Managing phenology for agronomic adaptation of global cropping systems to climate change

von
Sara Minoli

Dissertation
zur Erlangung des akademischen Grades
Doctor of Philosophy
(PhD)

im Fach Agrarwissenschaften
eingereicht an der
Lebenswissenschaftlichen Fakultät
der Humboldt Universität zu Berlin

Präsidentin der Humboldt Universität zu Berlin
Prof. Dr.-Ing. Dr. Sabine Kunst
Dekan der Lebenswissenschaftlichen Fakultät
Prof. Dr. Bernhard Grimm

Gutachter:
1. Prof. Dr. Hermann Lotze-Campen
2. Prof. Dr. Reimund Paul Rötter
3. Dr. Christoph Müller

Tag der wissenschaftlichen Aussprache: 14.02.2020

Berlin, 2020

Zusammenfassung

Der Klimawandel erfordert eine Anpassung der landwirtschaftlichen Anbausysteme, um das derzeitige Produktionsniveau aufrechtzuerhalten oder gar zu verbessern. Trotz einiger positiver Effekte, die sich aus einer höheren Konzentration von CO_2 in der Atmosphäre ergeben könnten, wird erwartet, dass zukünftige Trends bei Temperatur und Niederschlag die Ernteproduktivität (Ertrag und Produktion) beeinträchtigen, insbesondere in Regionen, die bereits heute durch hohe Temperaturen und Wasserknappheit gekennzeichnet sind. Andererseits wird erwartet, dass eine wachsende Bevölkerung und eine veränderte Ernährung den weltweiten Getreidebedarf anfachen. Es besteht daher ein großes Interesse an der Erforschung möglicher Lösungen zur Anpassung der Anbausysteme an den Klimawandel unter bestmöglicher Nutzung der verfügbaren Kenntnisse, Ressourcen und Technologien.

Pflanzenmodelle sind die meist genutzte Methode zur Abschätzung zukünftiger Auswirkungen des Klimawandels auf die globale Pflanzenproduktivität. Lange Zeit wurden Studien zur Pflanzenmodellierung durchgeführt, ohne Änderungen in der agronomischen Bewirtschaftung zu berücksichtigen, die Landwirte als Reaktion auf den Klimawandel durchführen könnten. Der Hauptgrund hierfür ist der Mangel an Daten zu Bewirtschaftungspraktiken, insbesondere auf globaler Skala. Dies wird begleitet von einem geringen Verständnis darüber, wie agronomische Entscheidungen getroffen werden und wie sie sich im Laufe der Zeit verändern. Die zunehmende Verfügbarkeit globaler Bewirtschaftungs-Datensätze ermöglicht eine Verbesserung der historischen und gegenwärtigen Einschätzungen der Ernteproduktivität. Um jedoch Einsichten darüber zu gewinnen, wie sich die Bewirtschaftung in Zukunft verändern könnte, ist mehr Forschung erforderlich.

Ziel dieser Arbeit ist es, das Wissen über die Anpassung von weltweit relevanten Getreidepflanzen an den Klimawandel zu erweitern. Die zentrale Fragestellung ist, ob globale Anbausysteme an den Klimawandel angepasst werden können, indem die Phänologie der Kulturpflanzen durch Anpassung von Wachstumsperioden und Sorten gesteuert wird. Während Fortschritte beim Verständnis der Aussaatentscheidung erzielt wurden, bestehen große Wissenslücken in Bezug auf die Auswahl von Pflanzensorten, die in dieser Arbeit angegangen werden.

Der erste Schritt in der Analyse besteht in der systematischen Bewertung der Phänologie und der Ertragsreaktionen auf Temperaturanstieg und Sortenselektion unter Verwendung eines Ensembles von globalen, räumlich expliziten landwirtschaftlichen Modellen („Global Gridded Crop Models"). Die Ergebnisse zeigen, dass die Phänologie ein entscheidender Mechanismus für Temperatureffekte auf die Ernteerträge ist und dass die Verwendung von Sorten, die die ursprünglichen Wachstumsperioden einhalten, eine wirksame Strategie ist, um temperaturbedingte Produktionsverluste bei der Ernte auszugleichen. Ein vollständiger

Ausgleich ist jedoch nur bis zu 2 K Erwärmung (global gleichmäßiger Temperaturanstieg in Raum und Zeit) und anschließender Abkühlung möglich. Darüber hinaus wird in dieser Studie die Komplexität der Anpassung durch phänologisches Management herausgestellt, die den nächsten Analyseschritt motiviert.

Hier wird ein neuartiger Ansatz vorgeschlagen, um die Entscheidung der Landwirte für die Auswahl der dem lokalen Klima angepassten Anbauperioden zu formalisieren. Das Ergebnis der Analyse ist ein regelbasierter Algorithmus, der phänologische Zyklen der Kulturpflanzen auswählt, um die Zeit für die Ertragsbildung zu maximieren und Temperatur- und Wasserstress während der Wachstumszyklen zu minimieren. Diese Studie ergänzt bereits veröffentlichte Ansätze zur Simulation klimabedingter Aussaatdaten.

Schließlich werden regelbasierte berechnete Aussaattermine und Wachstumsperioden verwendet, um globale Muster von Sorten zu parametrisieren, die an aktuelle und zukünftige Klimaszenarien angepasst sind, und Auswirkungen auf die globale Pflanzenproduktion zu quantifizieren. Die Ergebnisse zeigen, dass eine regelbasierte Anpassung der Pflanzenphänologie dazu beitragen kann, die negativen Auswirkungen des Temperaturanstiegs abzumildern und die positiven Auswirkungen des CO_2-Düngungseffekts auszunutzen.

Insgesamt zeigt diese Arbeit, dass die Auswirkungen des Klimawandels auf die Ernteproduktivität erheblich variieren können, je nachdem, welche Annahmen zur agronomischen Bewirtschaftung getroffen werden. In allen hier untersuchten Fällen liefern Szenarien, in denen Änderungen im Management vernachlässigt werden, die pessimistischste Prognose für die zukünftige Pflanzenproduktion. Relativ einfache Ansätze zur Berechnung angepasster Aussaatdaten und Sorten bieten eine Grundlage für die Berücksichtigung autonomer Anpassungsschemata als integraler Bestandteil globaler Modelle.

Abstract

Climate change is posing a challenge to current cropping systems, if production levels are to be maintained or even enhanced. Despite some positive effects that might derive from higher concentrations of CO_2 in the atmosphere, future trends in temperature and precipitation are expected to negatively impact crop productivity (yields and production), especially in regions that are, already today, characterized by high temperatures and water shortages. On the other hand, growing population and changing diets are expected to force up the global demand for agricultural products. Therefore, exploring possible solutions for the adaptation of cropping systems to a changing climate is of high interest, making best use of the available knowledge, resources and technologies.

Crop models are the most frequently used method for estimating future climate change effects on global crop productivity. For long, crop modelling studies have been conducted without accounting for changes in the agronomic management that farmers might implement in response to climate change. This omission has been caused by data scarcity on management practices, especially at the global scale. This has come along with a low level of understanding on how agronomic decisions are taken and how they evolve over time. The increasing availability of global management datasets allows for an improvement of historical and present crop productivity estimates. Yet, to provide insights in future management changes, more research is needed.

The aim of this thesis is to advance knowledge on the adaptation of world-wide relevant grain crops to climate change. The central research question is whether global cropping systems can be adapted to climate change by managing crop phenology through adjusting growing periods and cultivars. While advancements have been made in understanding sowing dates decision making, large knowledge gaps exist on crop cultivar choice which will be addressed by this thesis.

The first step in the analysis is to systematically assess phenology and yield responses to temperature increase and cultivar selection, making use of an ensemble of Global Gridded Crop Models. Results show that phenology is a key mechanism of temperature impact on crop yields and that the use of cultivars that maintain original growing periods is an effective strategy to compensate temperature-induced crop production losses. Yet, full compensation is possible only up to 2 K of warming (globally uniform temperature increase in space and time) and declines thereafter. Moreover, this study emphasizes the complexity of adaptation via phenological management, motivating the next step of the analysis.

In the second study, a novel approach is proposed to formalize farmers' decision-making for choosing cropping periods adapted to local climate. The outcome of the analysis is a rule-based algorithm that selects crop phenological cycles aiming at maximizing the time

for yield formation and minimizing temperature and water stresses during the crop growth cycles. This study complements previously published approaches to simulate climate-driven sowing dates.

Finally, rule-based computed sowing dates and growing periods are used to parametrize global patterns of cultivars adapted to present and future climate scenarios and to quantify their effects on global crop production. Results indicate that rule-based crop phenology adaptation can aid alleviating negative impacts of temperature increase and help exploiting positive effects due to the CO_2 fertilization effect.

Overall, this thesis demonstrates that the impacts of climate change on crop productivity can vary substantially, depending on which assumptions are made on agronomic management. In all cases explored here, scenarios that neglect any changes in management return the most pessimistic projection on future crop production. Relatively simple approaches to compute adapted sowing dates and cultivars provide a base for considering autonomous adaptation schemes as an integral component of global scale modelling frameworks.

Acknowledgements

While writing this thesis, I received support from many people that I would like to sincerely acknowledge.

First and foremost, I feel fortunate for working at PIK and I am thankful to Christoph Müller, Hermann Lotze-Campen and all others that have given me this invaluable opportunity. Especially, I would like to express my deep gratitude to Christoph Müller for having provided guidance and motivation throughout my PhD project. I have greatly appreciated our stable and fruitful collaboration, without which this thesis would not have been possible. I also owe him the overarching research project (MACMIT), which through BMBF, has been funding my work for the whole period. It has been an exciting experience to undertake this path, together with my colleagues Femke Lutz, Vera Porwollik and Tobias Herzfeld.

The papers that compose this thesis are the result of continuous interactions with many co-authors. I would like to thank them all for their precious support, which helped me extricating the tangle of initial research ideas and extracting the essence from the results. Especially, I would like to thank Christoph Müller, Joshua Elliott, Tom Pugh, Jonas Jägermeyr and the entire GGCMI group. My work was made possible by their determined and unceasing endeavors for advancing global crop modelling standards. Collaborating with them has been insightful and also entertaining. I owe sincere gratitude to Dennis Egli for his generous and enlightening help on investigating crop phenology and for his encouraging messages. I am indebted to Susanne Rolinski, who has always supported and motivated my work throughout my PhD project.
I am deeply thankful to Susanne Rolinski, Xiaoxi Wang, David Chen, Jasmin Wehner and Isabelle Weindl for proofreading Abstract, Chapter 1, Chapter 2, Chapter 4 and Chapter 5 of this thesis, respectively. I have highly appreciated the expert guidance from Xiaoxi Wang, Bernhard Schauberger and Christoph Gornott on the doctoral procedures and formalities. Moreover, thanks to all colleagues that have been helping my work by providing content-wise and technical advises. Thanks to Frank Wechsung for his lively criticism.
I take this opportunity to thank Hermann Lotze-Campen, Reimund P. Rötter and Christoph Müller for accepting to review my PhD thesis.

Conducting research within the Land Use group has been a very enjoyable experience and an added value to my day-to-day work. The constructive, friendly and open-minded atmosphere of this team has sustained my motivation and enthusiasm, also in difficult times. My special -Thank you!- goes to Femke. Her irresistible humor and smile have been a medicine and a drug in these years. I am greatly fond of our reciprocal understanding and cooperation.

Thanks to Susanne, for encouraging communication and sociality within the group, for being inclusive and welcoming and for offering timely assistance. Thanks to Benni for his inspiring science and enthusiasm. I enjoyed our chats, the spontaneous dives in the lakes, and the improvised micro-holidays. Thanks to Bernhard, prodigious scientist and warmhearted gentleman. I would also like to thank Feli, Kristine, Isabelle, Mishko, Marie, Ge, Ewerton, Eleonora, Amsalu, Jannes, Stephen, Fabian, Constanze, Efi, Matteo, Marianna, Albano, Oscar and the many people at PIK with whom I have been sharing thoughts, fun and relaxed time.
I wish to acknowledge the highly professional and generous work conducted by scientific coordinators, IT-team, librarians and caretaker-team, which is a fundamental part of the optimal working environment that I have found at PIK.
I have also received great assistance by many anonymous contributors of the Stack Exchange online forums for computer programming, which I have been intensively consulting.

I am thankful to Marco Acutis and Marco Carozzi. Their encouragement and guidance has been fundamental for commencing new scientific and life paths.
To my new and old good friends, Simo, Macca, Laura, Wei, Giorgia, Femke, Antoine, Marco, Fra, Marti, Miky, Bene, Silvia R., Laura F., Tommi and Pietro, I want to express my deepest sense of affection and esteem. Your presence has been my strength in these years. Thanks also to Isacco and Noce for having shared with me important steps of my life.

I wish to thank my families, Mamma, Papá, Lucia, Marco and Marie. My words are not enough to reveal the gratitude for the values and love I have received from you and for having unconditionally been standing with me all these years.

On the most marvelous trail along this route, I have been walking with Nima. To him I dedicate my happiest thoughts.

Table of Contents

List of Figures

List of Tables

1

Introduction

1.1 Studying the Earth System – a global and multidisciplinary perspective

The term Earth System has been defined as "the suite of interacting physical, chemical and biological global-scale cycles and energy fluxes that provide the support system for life at the surface of the planet" (Steffen, Crutzen, and McNeill, 2007). The concept was introduced after recognizing the importance of the close interlink between the geophysical and biological spheres in defining the status of the planetary environment where the human society lives. The recent rapid global social and environmental changes have raised awareness on the crucial role played by humans within the Earth System processes.

The contemporary human society has been developing over the past 10 000 years, during a geological epoch, the Holocene, characterized by a relatively stable biophysical environment (Steffen et al., 2015) (Fig. 1.1). During this time, humans have affected the functioning of the Earth System at the global scale, with impacts variable in time and space (Certini and Scalenghe, 2015). Starting from the Industrial Revolution (ca. 1800 A.D.), human impacts have gained magnitudes large enough to effectively push the planet outside the range of variability of the Holocene, possibly into a new geological epoch. Due to the central role played by humans, this new epoch has been called the Anthropocene (Steffen, Crutzen, and McNeill, 2007; Rockström et al., 2009a), and it is characterized by a much warmer and biotically different state of the Earth System (IPCC, 2013; Steffen et al., 2016). Although the paleo-climatic records show that warmer greenhouse states of the Earth System have already occurred, such conditions have never been experienced during the Prehistory and History of the Homo sapiens (Steffen et al., 2016) (Fig. 1.1). Therefore, it is not known yet whether humans will be able to survive on a changing planet and in this case, how society will evolve and cope with the dual role of being at the same time drivers of global changes and an endangered species. Science is addressing these questions by describing and quantifying (i) how far are humans pushing the Earth System away from the Holocene; (ii) how heavily this changes will feedback on ecosystems and human society; (iii) what is the humans' capacity to survive and further develop under such new conditions? These questions are not exclusively of interest for science, but have also large practical implications for each individual person, to an extent that they have also become central in the public debate and at the political and global governance levels. In 2015 the United Nations have adopted 2030 Agenda for Sustainable Development (United Nations, 2015a), setting seventeen goals to tackle climatic and ecological challenges, along with social justice and improved wealth. Therefore, a big challenge of contemporary science is to integrate knowledge across several scales and disciplines of the Earth System, connecting together biophysical and socio-economic dimensions of this complex and dynamic system (Schellnhuber, 1999; Schellnhuber, Frieler, and Kabat, 2013).

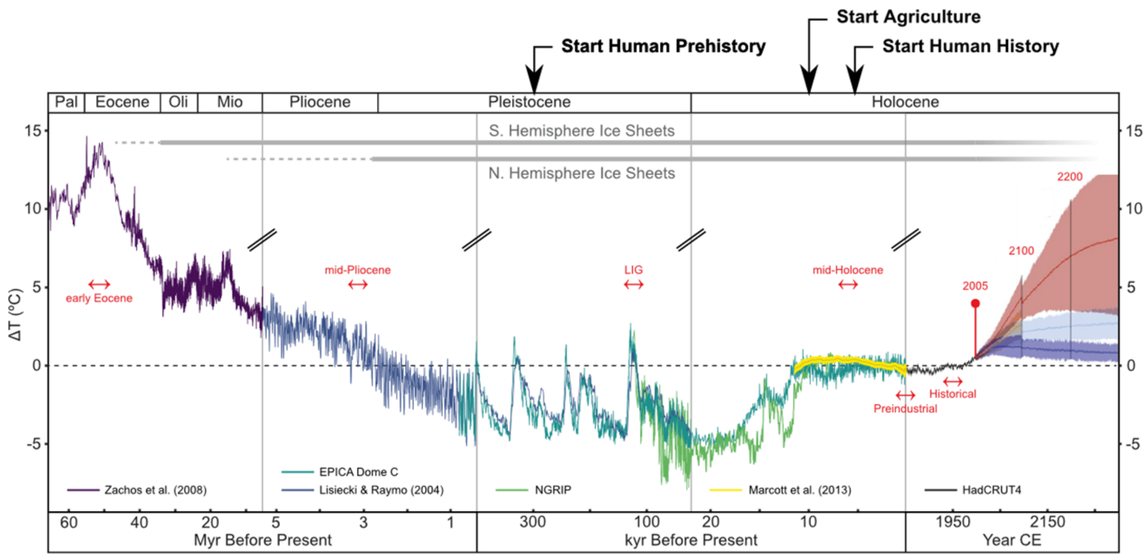


Figure 1.1: Temperature anomalies relative to 1961-1990 global means over the past 65 Million years and future projections for four Representative Concentration Pathways (RCPs 2.6, 4.5, 6.0, 8.5). Warm epochs and more recent periods that offer possible climate analogs for the future are indicated by red arrows (modified from Burke et al. (2018)). Black arrows indicate approximate dates of human (pre-)history events (History of the world in Wikipedia, 2019).

1.2 The food sub-system under the current global changes

Humans are part of the biosphere and share with the other living organisms those processes that are critical to sustain life on the Earth, such as the exchange of energy and matter (Miller, 1976) within the global food web (Strong and Frank, 2010). The food sub-system is at the base of the human livelihood, health, economy and culture. It aims at producing all necessary macro- and micro-nutrients in sufficient quantities and distributing food to each individual person. It includes several biophysical and socio-economic activities, in the first place agricultural production of crops, livestock, fisheries, and wild foods. Moreover it requires the manufacturing and distribution of inputs (seed, animal feed, fertilizers, pest control); food processing, packaging, storage, transport and distribution; marketing and retail; catering; domestic food management; and waste disposal (Vermeulen, Campbell, and Ingram, 2012).

1.2.1 The economics of food production

Food production is driven by food demand, which depends on population dynamics, on wealth level and distribution, and on people's diets, such as the share of plant- and animal-based products consumed (Bodirsky et al., 2015; Food and Agriculture Organization, 2018).
Food production is constrained by biophysical, technological and socio-economic limitations. The ability of producing food depends on the continued functioning of the biophysical system (Willett et al., 2019), of which constrains include climatic conditions, land availability, land fertility and water resources. Although agriculture is the result of the trial-and-error daily farmers' practice, its history is strongly coupled with scientific knowledge and technological progress. In the past, technological innovation has considerably increased the productivity of agricultural systems per unit of land (Ray et al., 2013). The most prominent example has been the so called Green Revolution (started in the 1960s), which within only 40 years has doubled agricultural production through the intensification of the production factors, such as genetically improved varieties, synthetic fertilizers, irrigation and mechanization (Khush, 2001).
The production of agricultural goods is tightly coupled with the micro- and macro-economy, and thus with fluctuations of food prices (Nelson et al., 2013), land use patterns (Schmitz et al., 2014), farm structure and size (Herrero et al., 2017), access to the market and policies (Verburg, Ellis, and Letourneau, 2011). Global food demand is projected to strongly increase in the future decades (Godfray et al., 2010) with a shift in diets towards animal-based products (Bodirsky et al., 2015), which will push the food system to both increase production and escalate the scarcity of limited resources.

1.2.2 Food production contribution to global environmental changes

Food production is among the largest causes of global environmental changes (Willett et al., 2019). In order to produce food and other agricultural services, humans have been converting large portion (∼40%) of the global terrestrial ecosystems to cropland and grassland. This has generated a wide range of effects on both the physical and biological spheres (Foley, 2005). Cropland has been partly or completely replacing natural landscapes. This, in most cases, has been causing a decline in biodiversity and loss of habitats for many species, up to their extinction (Molotoks et al., 2018).
Agriculture uses large volumes of water. Although most of the current cropland is still rainfed (the area equipped for irrigation is only 18% (Portmann, Siebert, and Döll, 2010)), there has been a rapid increase in area equipped for irrigated land since 1900 (Siebert et al., 2015). Water consumption in the agriculture sector competes with water demand from other sectors, as well as with natural ecosystems. Water withdrawal for human activities subtracts this resource from ecosystems that often go below the water flow required for their own health and maintenance (Gerten et al., 2013). Land use has also large impacts on the global biogeochemical cycles. The clearance of natural vegetation and the harvest of biomass modify natural carbon fluxes and stocks (Wolf et al., 2015; Balesdent et al., 2018). The cultivation of soils reduces biomass input through harvest and increases mineralization rates, with a consequent decline in soil organic matter content (Lal, 2004). Moreover, the application of fertilizers to provide nitrogen and phosphorous as macro-nutrients to the cultivated crops,

generates a cascade of detrimental effects on the surrounding natural ecosystems as well as on natural resources of primary importance for human societies, as fresh water bodies (Galloway et al., 2003).
The modification of the biogeochemical cycles has direct impacts on the main drivers of climate change. Deforestation and soil cultivation contribute to the CO_2 enrichment of the atmosphere, which is the main driver of global temperature increase (IPCC, 2013). Moreover, land use has been amplifying the seasonal cycle of atmospheric CO_2 concentration (Zeng et al., 2014). Agriculture is the main emission source of non-CO_2 greenhouse gasses. Ruminants and paddy rice cultivation are among the largest anthropogenic sources of methane (CH_4), while the application of nitrogen fertilizers is the major source of nitrous oxide (N_2O) emissions (IPCC, 2013). Land-cover and land-use change directly affect the surface energy balance from local to global scale by changing the properties of the vegetation cover and seasonality in terms of albedo, roughness and evapotranspiration fluxes, which can either mitigate or deteriorate climate change effects (Sacks and Kucharik, 2011; Davin et al., 2014; Li et al., 2016; Erb et al., 2016; Lombardozzi et al., 2018).

Food production therefore needs to develop towards sustainable practices. A considerable amount of studies are investigating options for improving agricultural sustainability, in order to maintain its own functions as well as to safeguard the other ecosystems and human health (Pretty, 2008). Sustainable Intensification is widely proposed as a win-win strategy to both achieve human well-being and to protect the environment, although it is difficult to simultaneously attain benefits across multiple social-ecological dimensions due to the existing trade-offs between them (Rasmussen et al., 2018). It is also proposed that the demand-side processes (food diets, consumption, waste) may also need to be managed in order to lower their negative environmental impacts, by e.g. reducing animal-based food consumption (Rockström et al., 2009b; Food and Agriculture Organization, 2018). Overall, to be effective in increasing the sustainability of the food system, different strategies from shifting towards healthy diets, sustainable agricultural intensification and reduction of food losses and waste should be implemented and coordinated across different scales from individual choices, local policies and intergovernmental efforts (Willett et al., 2019).

1.2.3 Resilience and adaptation of agricultural systems to climate change

The human-induced changes in the Earth System feedback to the human systems themselves. The massive emission of greenhouse gasses and the modification of the surface energy balance produced by human activities have been altering the natural state and variability of the global climate, a process that is defined as climate change attributable to human activities (IPCC, 2013). Agricultural primary productivity is highly dependent on atmospheric composition, weather and climate, and it is therefore sensitive to climate change.
The recent past has been characterized by significant trends in some climatic variables that play a role in crop productivity. The atmospheric CO_2 mole fraction has been increasing from 278 ± 5 ppm in 1750 (IPCC, 2013) to more than 400 ppm of the present day (Dlugokencky and Tans, 2019). Starting around the end of the 19th century, the global mean surface temperature has been progressively rising (IPCC, 2013) reaching approximately 1 °C of

warming in 2017 (IPCC, 2018). Higher temperatures intensify the global hydrological cycle, with higher evaporation rates and increased global precipitation. Trends in global temperature and precipitation are, however, different across regions and seasons. Surface temperature increase has been faster on land than on the oceans and at higher latitudes than in the tropics (IPCC, 2013). Moreover, rainfall patterns are being exacerbated with precipitation increasing in already wet regions and decreasing in the dryer subtropical regions (Rojas et al., 2019). Climate change is also detected by the frequency of extreme events, which, for instance, in Europe has been found to be much higher now that just a few years ago (return time of extremely hot summer is ten times smaller now than in the early 2000s) (Christidis, Jones, and Stott, 2014). Future projections indicate that even if ambitious efforts were immediately undertaken at both the societal and policy level to drastically reduce net greenhouse gas emissions, it would not be possible to completely arrest climate change (IPCC, 2018), due to the thermal inertia of the Earth that delays its responses to climate forcings (Hansen, 2005).

Agricultural systems are dynamic, as they continuously co-evolve with their biophysical and socio-economic environment (Schiere, Darnhofer, and Duru, 2012). Climate change is rapidly modifying the environmental conditions (most importantly CO_2, temperature and precipitation) of global agricultural systems, posing risks to food production and additional challenges on top of those regarding environmental sustainability and production increase.
Crop yield is the most widely used metric to quantify the productivity of cropping systems. It is defined as the weight at some agreed standard moisture content of harvestable product (grain or other plant parts of economic interest), per unit of land area harvested per crop cycle (usually reported in t ha^{-1}). Yield is measured at different scales (plot, field, farm, district, region or country) and for different purposes (economic value, scientific experimentation, statistics reports) (Fischer, 2015). To quantify food-crops productivity, yields can eventually be converted into calories, as this unit better reflects the value of the food in terms of its energy content, although still too simplified to reflect the complexity of food nutritional values (Müller, Elliott, and Levermann, 2014; Willett et al., 2019). Yield is built through plant growth (primary production) and phenological development (progress through life-cycle phases). Primary production is the result of the plant biochemical conversion of energy (solar radiation), water, atmospheric carbon dioxide (CO_2) and mineral nutrients into organic biomass, which is then allocated to different organs (roots, leaves, flowers, and grains). Phenological development determines the time available for primary productivity and the transition of the plant between life-cycle phases, characterized by different plant structural features and functions (e.g. canopy expansions, grain filling) (Egli, 2011).

Being sessile organisms, crops are exposed to the large range of environmental conditions and have to cope with a series of stresses that limit their productivity.
Atmospheric CO_2 is essential for plant primary productivity, being the primary reagent of photosynthetic reactions. The C_3 and C_4 are the two main photosynthetic pathways relevant for agricultural crops (von Caemmerer, 2000). Crops grown under higher CO_2 concentrations generally show higher yields, a phenomenon called CO_2 fertilization. The effect is due to a decreased photorespiration and partial stomatal closure, which limits transpiration. The

effect is more pronounced in C_3 species, whereas C_4 species that have a mechanism to minimize photorespiration, are advantaged only under water limiting conditions due to the increase in water use efficiency (Long et al., 2005; Kimball, 2016).
Crops are exposed to ambient temperatures occurring in the location where they grow and they can only partially self-regulate their internal temperature. Temperature affects directly or indirectly all biochemical reactions and physiological processes that take place in the plant growth , such as phenology, transpiration, photosynthesis, respiration (Sage and Kubien, 2007; Parent et al., 2010; Parent and Tardieu, 2012). Studies conducted at various scales and with different methods, have shown that increases in average daily temperature generally cause reduction in crop yields (Lobell, Schlenker, and Costa-Roberts, 2011; Asseng et al., 2014; Zhao et al., 2017). Under global warming crops will be also exposed to critically high temperatures (Gourdji, Sibley, and Lobell, 2013; Teixeira et al., 2013), which can irreversibly damage the crop tissues and organs, especially during the reproductive phases of development when yield is being formed (Barnabás, Jäger, and Fehér, 2007; Hatfield and Prueger, 2015).
Plants uptake water from soil and release it to the atmosphere through the stomata in a process called transpiration, which is essential for nutrient uptake and solutes transport within the plant as well as for regulating the temperature of the plant tissues. Water and its management is therefore crucial in agricultural fields (Passioura, 2006; Bodner, Nakhforoosh, and Kaul, 2015). Precipitation deficit and drought have large impacts in reducing primary productivity (Ciais et al., 2005) and crop yields (Daryanto, Wang, and Jacinthe, 2017; Glotter and Elliott, 2016). Precipitation distributions are expected to become more uneven under climate change affecting future crop yields (Fishman, 2016).

Resilience is “the capacity of a system to absorb disturbances and reorganize while undergoing changes” and therefore to persist despite the occurrence of new conditions (Walker et al., 2004). The resilience of agricultural systems under climate change depends on their capacity and ability to buffer disturbances, adapt and transform (Folke et al., 2010). Adaptation to climate change has been defined as the process of adjustment to actual or expected climate and its effects in order to moderate or avoid harm or to exploit beneficial opportunities. Adaptation can be *incremental* or *transformational* depending on whether the actions maintain or drastically change the attributes of a system (IPCC, 2014; Kates, Travis, and Wilbanks, 2012). Adaptation can also be either *autonomous* or *planned*, depending on whether the necessary measures already exist and can be directly implemented by farmers, or whether before taking actions it is necessary to assess their costs and benefits, a process that requires the collaboration of e.g. practitioners, scientists and policy makers (Füssel, 2007). *Incremental* and *autonomous* adaptations to climate change typically include adjustments of agronomic practices, such as shifting sowing dates; choosing genotypes with more appropriate phenology or stress tolerance; altering fertilization and irrigation practices; using in season weather forecasts for better planning of agronomic interventions; and the introduction of insurance systems for farmers (Ainsworth and Ort, 2010; Olesen et al., 2011).
Transformational adaptation requires instead more profound modifications of the production system (Kates, Travis, and Wilbanks, 2012) that can take place at the farm scale by e.g. crop diversification, soil management, water harvesting (Altieri and Nicholls, 2017) or at larger scales such as land-use change or crop-land expansion.

1.3 Scientific investigation of agricultural systems under climate change

Scientific research has progressively become indispensable for understanding ongoing global changes and for exploring possible ways forward for human societies. Scientific evidences are nowadays the base for discussing, negotiating and implementing climate change policies. The Paris Agreement, where countries recognized "the urgent threat of climate change on the basis of the best available scientific knowledge" and agreed upon "undertaking ambitious efforts to combat climate change and adapt to its effects" (UNFCCC, 2015) is a manifest example. In this context, the ability of agriculture to continuously and sustainably produce food is a central concern for governance at local to global levels (United Nations, 2015a; Food and Agriculture Organization, 2018).

The scientific investigation of agricultural systems under climate change is generally conducted along three disciplinary lines of research: 1) climatology, studying the physics of the climate system and how it evolves under changing forcings, including the feedback from land use activities (e.g. increasing greenhouse gas emissions, change in albedo) (Taylor, Stouffer, and Meehl, 2012); 2) agroecology, studying the biophysical effects of climate and human management on agro-ecosystems (Tomich et al., 2011); 3) agricultural economics, studying the economic consequences of climate change on agricultural sectors and the responses of economic actors (McCarl and Hertel, 2018). A further step consists in integrating disciplinary knowledge into comprehensive approaches in order to study the chain of impacts from climate to human systems and their feedback (Nelson et al., 2013; Frieler et al., 2017b). This thesis is a disciplinary contribution to agroecology, but the methodological approaches and the findings are defined and discussed to inform the broader frame of integrated studies.

1.3.1 The agro-ecological perspective

From a natural sciences perspective, agricultural systems are terrestrial ecosystems in which humans intervene by controlling physical (soil fertility) and biological (species composition) factors in order to produce food or other goods (Robinson, 2014). Agroecology applies ecological concepts and principles to study the interactions between plants, animals, humans and the environment within agricultural systems, and to design and manage sustainable food systems (Dalgaard, Hutchings, and Porter, 2003; Gliessman, 2014).

The study of agroecosystems necessarily (although not solely) considers primary productivity as a central variable of interest. Yield is a highly integrated trait and its response to the external factors is the combined response of all underlying yield components (e.g. number of spikes, spike length, seeds per spike, individual seed weight) and determinants (e.g. root extent and leaf area) that are sensitive to those factors (Parent et al., 2017). The many macro- and micro-environmental conditions to which the plant is exposed during its life (or annual) cycle determine the yield gain of a given growing season. Such conditions can be limiting, generating stresses that reduce growth and ultimately the yield. Abiotic stresses include low or high temperatures, deficit or excess of water and nutrients, low or high light intensity, air pollutants and toxic substances. Plant responses to stresses are dynamic and complex, as they involve multiple phases and pathways from stress reception to signaling and processes regulation (Cramer et al., 2011). Yield is hence variable from year to year depending on the interaction of three main components: genotype (G), the heritable information carried by the plant genome, environment (E), mainly weather, soil physics and chemistry, biotic factors (e.g. parasitism, symbiosis or mutualisms with other living organisms) and management (M) agronomic practices applied by the farmers (Schauberger, Rolinski, and Müller, 2016; Chenu et al., 2017; Rötter et al., 2018).

One key research challenge within contemporary agroecology is to connect agricultural and environmental sciences, in order to understand the relationships between field-level agroecological processes and broader environmental phenomena, such as climate change (Tomich et al., 2011). Research questions in this direction include: How climate change affects productivity of cropping systems? How does it influence agricultural management? And how can agricultural management be designed to make the best use of available natural resources in order to sustainably produce food?

1.3.2 Scientific methods to study the agroecosystems

Direct experimentation is the basis of research in agricultural sciences. Agronomic trials, where crops are grown under different management settings, have been intensively used to evaluate productivity performances of cropping systems, and then extended to assess the effects on e.g. soil fertility and environmental pollution. Experiments are however slow, labor intensive, and affected by the large number of variables that cannot be controlled for in a complex ecological system. Moreover the experimental design becomes very complex as soon as additional environmental and social dimensions are considered (Antle, 2019).
In the 1960s, when computational tools and power started taking off, agricultural sciences conceived the first crop models to quantify the responses of the crops to complex sets of conditions. Since then, crop models have been developed for a wide range of purposes such as to increase the understanding of the soil-plant-atmosphere processes, as decision-support systems from farm to regional scales, to assess and guide sustainable development of agro-ecosystems and to assess climate change effects on agricultural productivity (Di Paola, Valentini, and Santini, 2015; Fath, 2018; Chenu et al., 2017). Crop models are generally classified, although with some overlap, as either statistical or process-based models (Schils et al., 2012; Jones et al., 2017; Lobell and Asseng, 2017). These two model types differ in their methods and scope.
Statistical crop models consist of direct functional relationships, built between explained and explanatory variables. To estimate effects of climate change on crop yields, these models use regression techniques trained on historical yields and aggregated input variables, such as growing season average temperature or precipitation (Lobell and Burke, 2010). To account for the complexity of the systems, statistical techniques have been developed to build models based on multiple explanatory variables simultaneously. The main objective of such models is to accurately predict yields and to quantify the relative influence of each explanatory variable and factor (Di Paola, Valentini, and Santini, 2015).

Process-based crop simulation models integrate the theories on individual processes (flow of energy and matter) primarily to conceptualize the functioning of agro-ecosystems (Porter and Semenov, 2005; Di Paola, Valentini, and Santini, 2015; Muller and Martre, 2019a). Each process is then represented by a mathematical function and by its interdependency with other processes. The mathematical functions can be statistical models themselves, of which the outcome is then integrated over e.g. time or space. Parameters in process-based models ideally have a biological meaning and a measurable unit. They estimate multiple output variables simultaneously (e.g. biomass growth and water consumption) (Rötter et al., 2018), therefore allowing for a more comprehensive assessment of the agroecosystems.

1.3.3 Modelling crop management for adaptation

Both statistical and process-based models are extensively used approaches to understand and anticipate the effects of future climate change on crop physiology and productivity. However, for projecting how cropping systems might evolve under future scenarios, a necessary further step is to investigate the evolution of production systems considering the strategies (crop breeding and agronomy) that farmers might use to cope with a changing environment (Challinor et al., 2018).

This thesis aims at investigating cropping systems adaptation to climate change by managing crop phenology from a global-scale perspective. For this purpose, process-based crop models have been chosen as method of analysis, as they are generally better suited than statistical ones for exploring agronomic and genetic adaptation (Lobell and Asseng, 2017). First, they allow mechanistic understanding of the processes underlying crop productivity, by explicitly representing soil-plant-atmosphere processes, interactions and feedbacks. Second, they estimate multiple output variables simultaneously, which allows for a combined analysis of yield and phenological outputs (e.g. maturity dates). Third and most importantly, they simulate the temporal evolution of crop growth within a single growing season. This is essential for exploring the responses of crop phenology to climate variables. There are a number of process-based crop models that are currently applied at the global scale to study climate change impact and adaptation. These have been developed from either site-based crop models or from ecosystem models. The former were originally developed to simulate crop yield responses to the environment and agronomic management, while the latter to simulate carbon, water and nutrient fluxes across global land areas, and included agricultural crop simulation in a second stage to improve representation of those dynamics (Rosenzweig et al., 2014; Müller et al., 2019).

1.3.3.1 Agronomic management information in crop models

Crop models require biophysical variables, such as atmospheric CO_2 concentration, weather variables, soil type, as input data. Additionally, they need information on a set of agronomic management practices and their schedule, which usually include crop growing periods, crop cultivars, irrigation and fertilizers (Rosenzweig et al., 2014). Some also considers soil tillage (Lutz, Stoorvogel, and Müller, 2019) and crop-residues management (Lutz et al., 2019). Although in principle, process-based models allow for representing such management practices

with a high level of detail, in practice it depends on information availability, model purpose and process understanding (Erb et al., 2016). Site-based crop models have been typically relying on experimental data and on the knowledge of the local farming practices. As opposed, models at the global scale retrieve information from globally compiled datasets, where possible, or need to define assumptions and scenarios on the temporal and spatial distribution of management practices (Rosenzweig et al., 2014; Elliott et al., 2015). The increasing number of global scale studies in agricultural sciences, has been driving up the demand of data on global agronomic practices to be used within various modelling frameworks (Makowski et al., 2014; McDermid, Mearns, and Ruane, 2017; Pongratz et al., 2017). Today datasets are available for land use (Portmann, Siebert, and Döll, 2010), crop growing periods (Portmann, Siebert, and Döll, 2010; Sacks et al., 2010), nitrogen (Conant, Berdanier, and Grace, 2013; Nishina et al., 2017), phosphorous (Powers et al., 2019), irrigation (Siebert et al., 2015), tillage types (Porwollik et al., 2019).
These data provide extremely valuable information for exploring mitigation and adaptation strategies to climate change. However, the technical implementation of such management effect into global crop models is often hampered by mismatches between the information detail reported in observation datasets and the detail of process representation in models (Pongratz et al., 2017). Often, data lack detail on within-growing season and inter-annual temporal variation, which are crucial in determining crop yields and environmental impacts (e.g. the same annual nitrogen application rate can be applied all in one event or split into smaller amounts during the growing season, determining a different nutrient availability for the crop and losses in the environment) (Hutchings et al., 2012; Erb et al., 2016). For some land management practices, such as crop species selection, even if datasets are available, the level of understanding of their effects and of how they vary across climate and soils hamper their implementation in dynamic modelling (Erb et al., 2016). Moreover, global-scale datasets are generally not purely observation based, but rather a hybrid product between observations, modelling techniques and assumptions for filling missing data (Portmann, Siebert, and Döll, 2010). This introduces uncertainty and limit their use for both process understanding and for model evaluation (Porwollik et al., 2017).

1.3.3.2 Implementing adaptation strategies in crop models

Observational data by definition refer to the past. In modelling exercises, in absence of a full understanding of their possible evolution, past management practices are assumed to remain unchanged also under climate change. Yet, in order to assess agronomic adaptation strategies to future climate it is necessary to implement changes in management practices too. A common modelling approach for adaptation assessments is to perform sensitivity analysis of crop productivity under different management scenarios and to identify which return the highest yield (Barbottin, Bail, and Jeuffroy, 2006; Bassu et al., 2009; Cammarano et al., 2012; Semenov et al., 2014; Zimmermann et al., 2017; Ruiz-Ramos et al., 2018). Management scenarios include sometimes more than one practice (e.g. sowing dates, cultivars and irrigation) so that packages of combined management practices and their interaction can be assessed to identify the best adaptation strategy (Cammarano et al., 2012; Rötter et al., 2013; Ruiz-Ramos et al., 2018). This approach however hampers the implementation of adaptation of cropping systems in the context of Earth Systems (McDermid, Mearns, and Ruane, 2017) or Integrated Assessment modelling (van Vuuren et al., 2009). The high number of simulations required becomes very expensive in terms of computational and data storage resources. Besides, it dramatically complicates the analysis, if the study does not specifically aim at comparing adaptation scenarios, but rather considers adaptation as part of a larger set of measures within a scenario (e.g. socio-economic pathways) (Challinor et al., 2018). The limits of the scenarios comparison approach can be overcome by a “modelling-the-manager” approach. This implies understanding the decision-making process underlying agronomic management practices, conceptualizing it into a model and dynamically implement this into crop modelling approaches (Aubry, Papy, and Capillon, 1998; Debaeke and Aboudrare, 2004; Dury et al., 2011a; Moore et al., 2014). Chapters 3 and 4 of this thesis present the development and application of an approach to simulate adapted crop cultivars at the global scale. A previous example of this kind has been published by Waha et al. (2012) on sowing dates. Alternatively, the model can be derived on a more empirical base, without thoroughly investigating the decisions underlying farming practices (Bondeau et al., 2007; Lindeskog et al., 2013; van Bussel et al., 2015; Mathison et al., 2018). The modelling-the-manager approach can shift the focus from creating artificial scenarios by trying all combinations of management options to creating scenarios that have different adaptation target (e.g. optimize the use of natural resources (Debaeke and Aboudrare, 2004)). Furthermore, it has some advantages in terms of simulating systems closer to their functioning in the “real world”. In fact, farmers operate and adapt their agroecosystem even in the absence or uncertainty of structured scientific knowledge (Hay, Porter, et al., 2006; Doré et al., 2011; Olesen et al., 2012). Therefore, they develop valuable experience-based knowledge that can help to adapt also if there is imperfect information transfer from scientific research, and that on the other hand can help science its self, identifying viable adaptation options (Doré et al., 2011). Consequently, being able to model current agronomic decision-making can help identifying opportunities that can be more easily received and adopted by farmers (Aubry, Papy, and Capillon, 1998).

1.3.4 Phenology: a key process in the interaction of crop, climate and adaptation

Phenology is the sequential production, differentiation, expansion and loss of structural units of the plant (Hay, Porter, et al., 2006). Phenology is affected by climate, genotype and management (Rezaei, Siebert, and Ewert, 2017; Rezaei et al., 2018). The timing of the phenological events (e.g. flowering) in the growing season is mainly driven by the responses to temperature per se, vernalization and photoperiod. The response of crops to these factors is genetically regulated and it is crop- and cultivar- specific. All crops and phenological phases are sensitive to temperature per se, but cardinal temperatures are considered crop-specific. Moreover, sensitivity to photoperiod and vernalization is very different across species, cultivars and phenological phases including complete insensitivity (Distelfeld, Li, and Dubcovsky, 2009; Slafer et al., 2015).

The time of sowing is purely management driven. It sets the starting point of the growing period and therefore determines the weather to which the crop growth cycle will be exposed (White et al., 2012). This affects the length of the subsequent phenological phases; the crop resources allocation to various yield determinants (e.g. rooting depth, number of leaves and or tiller, number of grains); and the risk of encountering stresses, such as frost or high temperatures (e.g. Hunt et al. (2019). The choice of species, cultivars and sowing dates are therefore fundamental management options to match the resources and limitation of the production environment and play a crucial role in adapting cropping systems to different regions and climates (Summerfield, Ellis, and Craufurd, 1996; Bassu et al., 2009; Kamran, Iqbal, and Spaner, 2014; Nakamichi, 2014). The adaptation of cropping systems to climate change therefore cannot do without understanding future crop phenological patterns and the strategic role played by agronomic management and breeding in building resilience capacity.

Dynamic crop models simulate both growth and phenological development. Models at the global scale have implemented very different levels of detail in the phenological stages represented, the most simple approach having a single phase from emergence to physiological maturity (Schaphoff et al., 2018), while more detail ones (Hank, Bach, and Mauser, 2015) can cover the entire BBCH scale (Meier, 1997) progression, which allows for coding up to 100 phenological stages. The development rate is expressed as a function of temperature, based on the thermal-time theory, eventually modified to account for vernalization and photoperiod responses (Hay, Porter, et al., 2006).
Crop models are thus suitable tools for exploring phenology responses to climate change. Moreover, they can be used to understand and guide management decisions, also for climate change adaptation. This is a relatively recent area of application, particularly in global scale modelling. If previous effort have developed modelling approaches to dynamically simulate sowing dates under changing climate, much less is known about the representation of cultivar diversity and spatial distribution (Chenu et al., 2017).

1.4 Scope and aims of the thesis

This thesis analyzes the role of phenology in the agronomic adaptation of global cropping systems under both present climate and future scenarios. The outline follows the three main objectives that have guided this work: (i) to study the effects of temperature increase on crop productivity and phenology (chapter 2); (ii) to model the agronomic management of crop phenology in response to climate changes (chapter 3); (iii) to quantify the capacity of decision-based phenology management for crop yield adaptation (chapter 4). The main motivation for this thesis is the need of an improved understanding of global cropping systems, as central components of the Earth System situated at the intersection between its biophysical and social spheres. Hence, the analysis is specifically conducted at the global scale and for crop types that are relevant both as staple food and for the extent of the area dedicated to their cultivation.

Chapter 2. In this study a large dataset provided by the state-of-the-art of Global Gridded Crop Models is used to conduct a sensitivity analysis of the simulated crop yields along two main dimensions: the air temperature and the crop management. In the baseline scenario, global patterns of crop yields are simulated under a historical weather time series and historical sowing dates and cultivars. Sensitivity to temperature is assessed by simulating yields under temperature-driven changes in crop phenology and growth under perturbed temperature, generated by adding progressively increasing temperature offsets to the historical weather (all other climate variables are unchanged). Crop growing periods and irrigation are analyzed as management practices to compensate negative effects of temperature increase. This work shows that taking into account adaptive management in global scale studies can substantially change the picture of climate change impacts on global crop production. Here adaptation is simulated in a very simplified way to allow the systematic separation of the temperature and management effects. Results, however, emphasize the complexity of adaptation strategies, which should be differentiated to target different geographical zones, to avoid new unfavorable conditions that can emerge within the baseline growing periods, and to exploit new opportunities that might come with climate change.

Chapter 3. This study represents the major conceptual advancement contributed by this thesis. It is motivated by the fact that the majority of current crop models do not consider the dynamic adaptability of management in cropping systems to a changing climate. The challenge extends beyond the availability of datasets on current farming practices. The aim is to increase the understanding of the underlying farmers' decision mechanisms in the management of crop phenology. The starting hypothesis is that farming practices (sowing dates) and plant traits selection (cultivars) co-evolve with local climate and environmental conditions, as a result of the trial and error learning process of farmers under the current technological advancement in which they operate. The outcome of this work is a rule-based model to mimic farmers' decision making in selecting suitable crop growing period under the location-specific climate in which they operate. The model is proven to be able to reproduce global patters of growing periods of major grain crops under historical climate and can be used to simulate phenology adaptation under any other climate scenario.

Chapter 4. This study uses the modelling approach presented in Chapter 3 to define adaptation scenarios under both reference and future climate. Global patterns of sowing and maturity dates are computed and used to derive phenological parameters that represent distributions of locally adapted crop cultivars. Sowing dates and cultivars are then used as model inputs to simulate daily phenological progress and crop yields by applying the LPJmL global gridded crop model. Counterfactual management scenarios are tested to verify the beneficial effect of cropping-periods adaptation. Adjusting both sowing dates and cultivars is found to globally increase crop production under future climate, alleviating climate change negative impacts and helping exploiting beneficial effects of CO_2 fertilization. Overall, the results of this study demonstrate the importance of accounting for farmers' decision making in bio-physical modelling of climate change impacts on crop yields.

1.5 Statement on contribution to thesis chapters

This doctoral thesis includes two manuscripts published in peer-reviewed journals, one unpublished manuscript. I, Sara Minoli, declare herewith to be the lead author of all chapters in this thesis[1]. Contributions, as detailed here below, have been confirmed in writing by all co-authors.

The thesis content and outline were conceived by Sara Minoli and discussed with Dr. Christoph Müller and Prof. Hermann Lotze-Campen. **Chapter 1** (Introduction) and **Chapter 5** (General summary and conclusion) were written by Sara Minoli. Dr. Christoph Müller provided comments on previous versions of these.

Chapter 2: Sara Minoli, Christoph Müller, Joshua Elliott, Alex C. Ruane, Jonas Jägermeyr, Florian Zabel, Marie Dury, Christian Folberth, Louis François, Tobias Hank, Ingrid Jacquemin, Wenfeng Liu, Stefan Olin, Thomas A. M. Pugh *Global response patterns of major rainfed crops to adaptation by maintaining current growing periods and irrigation.* Accepted on 3^{rd} September 2019 in Earth's Future. DOI: 10.1029/2018EF001130

S.M., C.M., J.E. and A.C.R. conceived the research questions and methods, which were discussed with all authors. While C.M., J.E. and A.C.R largely developed the GGCMI modelling protocol, S.M. predominantly developed the exact research question of this study and the corresponding analysis framework. C.M., J.E., F.Z., M.D., C.F., L.F., T.H., I.J., W.L., S.O. and T.A.M.P. provided model results. S.M. conducted the entire literature research and data analysis and also prepared all figures of the manuscript. S.M. predominantly developed the structure of the manuscript and wrote the entire manuscript, with smaller contributions from C.M., J.J., F.Z., T.A.M.P. All authors provided comments on the manuscript and S.M. assessed and incorporated these where suitable.

Chapter 3: Sara Minoli, Dennis B. Egli, Susanne Rolinski, Müller *Modelling cropping periods of grain crops at the global scale.* Accepted on 26^{th} December 2018 in Global and Planetary Change. DOI: 10.1016/j.gloplacha.2018.12.013

S.M. conceived the research questions with some guidance from C.M. S.M. developed and coded the entire modelling framework, with some feedback from C.M. D.B.E. contributed expert knowledge on plant phenology. S.M. conducted the entire literature research and data analysis. S.M. also prepared all figures of the manuscript. D.B.E. and S.R. provided comments on methods and analysis. S.M. wrote the entire manuscript, with smaller contributions from C.M., D.B.E. and S.R.

Chapter 4: Sara Minoli, Jonas Jägermeyr, Christoph Müller *Global crop yields benefit from adapting phenology to climate change.* Not yet submitted.

S.M., C.M. and J.J. conceived the research questions. S.M. and J.J. conducted model simulations. S.M. conducted the entire literature research and the full data analysis and prepared all figures. S.M. wrote the entire manuscript, with contributions from J.J. and C.M.

[1] In Chapters 2, 3 and 4 of this thesis the use of pronoun "we" indicates all co-authors that have contributed to each individual chapter.

2

Global response patterns of major rainfed crops to adaptation by maintaining current growing periods and irrigation

Sara Minoli[1,2,3,*], Christoph Müller[1], Joshua Elliott[4,5], Alex C. Ruane[6], Jonas Jägermeyr[4,6,1], Florian Zabel[7], Marie Dury[8], Christian Folberth[9], Louis François[8], Tobias Hank[7], Ingrid Jacquemin[8], Wenfeng Liu[10,11], Stefan Olin[12], Thomas A. M. Pugh[13,14]

[1]Climate Resilience, Potsdam Institute for Climate Impact Research (PIK), Member of the Leibniz Association, 14412, Potsdam, Germany

[2]Integrative Research Institute on Transformations of Human Environment Systems (IRI THESys), Humboldt-Universität zu Berlin, Unter den Linden 6, 10099, Berlin, Germany

[3]Albrecht Daniel Thaer-Institut für Agrar- und Gartenbauwissenschaften, Humboldt-Universität zu Berlin, Unter den Linden 6, 10099 Berlin, Germany

[4]Department of Computer Science, University of Chicago, Chicago, IL 60637, USA

[5]Center for Robust Decision-making on Climate and Energy Policy (RDCEP), University of Chicago, Chicago, IL, USA

[6]NASA Goddard Institute for Space Studies, New York, NY 10025, USA

[7]Department of Geography Ludwig-Maximilians-Universität München (LMU Munich), Munich, Germany

[8]Unité de Modélisation du Climat et des Cycles Biogéochimiques, UR SPHERES, Université de Liège, Quartier Agora, Allée du Six Août 19c, B-4000 Liège, Belgium

[9]International Institute for Applied Systems Analysis, Ecosystem Services and Management Program, Schlossplatz 1, A-2361 Laxenburg, Austria

[10]Eawag, Swiss Federal Institute of Aquatic Science and Technology, Ueberlandstrasse 133, CH-8600 Duebendorf, Switzerland

[11]Laboratoire des Sciences du Climat et de L'Environnement LSCE/IPSL, CEA-CNRS-UVSQ, Université Paris-Saday, F-91191 Gif-sur-Yvette, France

[12]Department of Physical Geography and Ecosystem Science, Lund University, Lund, Sweden

[13]School of Geography, Earth and Environmental Sciences, University of Birmingham, Birmingham, B15 2TT, UK

[14]Birmingham Institute of Forest Research, University of Birmingham, Birmingham, B15 2TT, UK

[*]Corresponding author

DOI: `https://doi.org/10.1029/2018EF001130`

Plain Language Summary

Global warming affects yields of grain crops, which are at the base of human diets. We use crop models to quantify its impacts on global crop production and to assess how adaptation could compensate for the adverse effects. We find that up to 2 K of increased temperature production can be maintained at the current level by using new cultivars, selected to maintain current growing period length under warming. Irrigation, as another management strategy, is shown to have the potential to increase yields in dry regions if water is available. However, models do not indicate that irrigation reduces the crops' sensitivity to warming. We find large differences in the yield response to warming and adaptation across climatic regions. While continental and temperate regions may benefit from higher temperatures, but also show sizable adaptation potentials, tropical and arid regions show largest temperature impacts and smaller adaptation potentials. After all, these two crop management options appear effective to balance the effects of moderate warming, but cannot fully compensate impacts above 2 K of warming.

Abstract

Increasing temperature trends are expected to impact yields of major field crops by affecting various plant processes, such as phenology, growth and evapotranspiration. However, future projections typically do not consider the effects of agronomic adaptation in farming practices. We use an ensemble of seven Global Gridded Crop Models (GGCMs) to quantify the impacts and adaptation potential of field crops under increasing temperature up to 6 K, accounting for model uncertainty. We find that without adaptation the dominant effect of temperature increase is to shorten the growing period and to reduce grain yields and production. We then test the potential of two agronomic measures to combat warming-induced yield reduction: (i) use of cultivars with adjusted phenology to regain the reference growing period duration; (ii) conversion of rainfed systems to irrigated ones in order to alleviate the negative temperature effects that are mediated by crop evapotranspiration. We find that cultivar adaptation can fully compensate global production losses up to 2 K of temperature increase, with larger potentials in continental and temperate regions. Irrigation could also compensate production losses, but its potential is highest in arid regions, where irrigation expansion would be constrained by water scarcity. Moreover, we discuss that irrigation is not a true adaptation measure, but rather an intensification strategy, as it equally increases production under any temperature level. In the tropics, even when introducing both adapted cultivars and irrigation, crop production declines already at moderate warming, making adaptation particularly challenging in these areas.

Keywords: temperature increase, crop yield, adaptation, growing period, irrigation, crop model.

2.1 Introduction

Productivity of current cropping systems can be severely affected by changes in climatic and weather variables (Challinor et al., 2014; Rosenzweig et al., 2014). Increasing temperature trends have already negatively impacted productivity of agricultural crops over the last decades (Lobell, Schlenker, and Costa-Roberts, 2011). Multiple methodologies consistently estimate that warming of one Kelvin causes between 3.1% and 7.4% decline in actual yields of major cereal crops, if no adaptation measures are undertaken (Challinor et al., 2014; Liu et al., 2016a; Zhao et al., 2017). Future projections indicate that large portions of current global harvested area will continue experiencing declines in the attainable yields, even under the assumption that management and technology could be transferred between regions, to areas where adaptation to climate change is most needed (Pugh et al., 2016).

Crop yield is a result of several physiological plant processes, many of which are mediated by the ambient temperature, as plants can only partially regulate their own temperature internally (Parent et al., 2010). Experimental evidence has shown that temperature increases up to a certain threshold level are associated with both accelerated rates of crop phenological development (the progress through the life cycle stages of the plant) (Parent and Tardieu, 2012; Hatfield, 2016) and growth metabolism (e.g. photosynthesis and respiration) (Atkin and Tjoelker, 2003; von Caemmerer, 2000). If higher metabolic rates enhance primary productivity (biomass) per unit of time, faster phenology also leads to shorter crop growing period durations (time from sowing to maturity), which are often associated with shorter grain-filling periods and thus lower crop yields (Egli, 2011; Hatfield et al., 2011b). High temperatures can reduce the net photosynthetic rate, because gross photosynthesis has a lower optimum than mitochondrial respiration (Yamori, Hikosaka, and Way, 2014). High temperatures also reduce the carboxilation rate of Rubisco, increasing photorespiration in C_3 species (Ainsworth and Ort, 2010). Extreme temperatures can also permanently damage plant tissues and reduce yields. Grain crops are especially sensitive during the reproductive phase (Porter and Gawith, 1999a; Hatfield, Wright-Morton, and Hall, 2018), undergoing floret sterility and disruption of the pollination process leading to lower grain numbers (Farooq et al., 2011; Hatfield, 2016), and a slower grain filling rate (Rezaei et al., 2015). Although the increase in air temperature alone is not a sufficient condition for increasing the evaporative demand, temperature is among the key drivers of evapotranspiration rates (Donohue, McVicar, and Roderick, 2010). Under non-limiting water conditions crop yields are enhanced by high rates of evapotranspiration, due to the coupled exchange of water and CO_2, increased by higher stomatal conductance. Vice versa, under limited water availability, if the increased evaporative demand cannot be fulfilled, stomatal conductance and hence yield is reduced (Passioura and Angus, 2010). Furthermore, higher evapotranspiration rates can deplete the soil water content faster, possibly leading to plant water stress (Bodner, Nakhforoosh, and Kaul, 2015). The evapotranspiration cooling effect is the main process of canopy temperature self-regulation (Kimball, 2016). Most process-based crop models include temperature response functions on the major physiological rates, while only a few include heat-stress impact mechanisms and the canopy temperature regulation (Asseng et al., 2015; Rezaei et al., 2015; Wang et al., 2017; Atkin et al., 2005; Smith and Dukes, 2013; Webber et al., 2017). Moreover, the combined effects of different stresses, such as temperature and water, which often occur simultaneously, are still poorly understood and pose a challenge for current global crop modelling (Chenu et al., 2017).

Different agronomic management options have been proposed as adaptation strategies against temperature-induced yield losses. Most commonly, these include a shift of sowing dates, choice of cultivars with adjusted phenology, and irrigation (Olesen et al., 2011; Challinor et al., 2014; Semenov et al., 2014; Tack, Barkley, and Hendricks, 2017; Ruiz-Ramos et al., 2018; Parent et al., 2018). Sowing dates can be advanced or delayed to match the most favorable thermal conditions and to exploit a longer growing season (Olesen et al., 2012; Sacks et al., 2010; Waha et al., 2012). Cultivars with higher thermal-unit requirements (temperature accumulation above a certain base temperature to reach physiological maturity), different vernalization requirements (exposure to cold temperatures to induce flowering), or altered photoperiod sensitivity (development response to day length) can be used to counteract the shortening of the growing period due to temperature increase (Sacks and Kucharik, 2011; Parent et al., 2018). In turn, shorter maturing cultivars can help avoid terminal heat- and water-stress (Mondal et al., 2013; Bodner, Nakhforoosh, and Kaul, 2015). Irrigation and other management strategies that increase soil moisture have the potential to compensate for the amplified evapotranspiration demand driven by temperature increase, but also to alleviate heat stress and accelerated phenological progress, by cooling the canopy temperature (Tack, Barkley, and Hendricks, 2017; Siebert et al., 2017; Webber et al., 2017). Although some studies assessed these adaptation strategies at local to regional scales (Semenov et al., 2014; Burke and Emerick, 2016; Ruiz-Ramos et al., 2018; Parent et al., 2018), their aggregated effects at the global scale remain an open question. Global projections of climate change impacts usually do not consider the adaptation potentials of agricultural system in response to climate change and might therefore overestimate impacts on crop yields and production.

Crop models allow for the conducting of virtual experiments to study the complex and interdependent biophysical effects of atmosphere and soil processes on crop growth and yield formation. As such, they are widely applied tools for the analysis of climate change impacts on agriculture and play a fundamental role in integrated assessment studies (Rosenzweig et al., 2018). Here we present the first spatially-explicit global study of the adaptation potential of the major staple crops to local temperature increase in rainfed systems. We use results from the Global Gridded Crop Model Intercomparison (GGCMI) within the Agricultural Model Intercomparison and Improvement Project (AgMIP) (Rosenzweig et al., 2013). The aims of the study are to assess the potential of adaptation in growing period selection and supplementary irrigation to avoid warming-induced reductions in crop yields. To this end, we study how uniform warming scenarios of 1, 2, 3, 4, and 6 K in each grid cell affect crop productivity and growing period duration. We then compare the impacts to a set of scenarios where hypothetical cultivars that maintain the reference growing period through adjusted phenology are introduced. As a second management measure we study the effect of converting rainfed into irrigated systems. Both interventions are analyzed separately and jointly. Since crop model responses are uncertain and models often show complementary skills (Müller et al., 2017), we employ an ensemble of seven GGCMs to address associated uncertainties. Model simulations are run according to a harmonized protocol, in terms of both weather inputs and agronomic management settings. The analysis is focused on the five major staple crops maize, winter wheat, spring wheat, rice, and soybean.

2.2 Materials and methods

2.2.1 Simulation protocol and models

Seven GGCM frameworks (CARAIB, GEPIC, LPJ-GUESS, LPJmL, pDSSAT, PEPIC, PROMET) contributed to this study (Table 2.1) and followed the GGCMI phase 2 simulation protocol (refer also to sections 1.1 and 1.2 of supporting materials[1]). The GGCMs are a class of process-based crop simulation models that are built to perform simulations on crop productivity and other agro-ecological variables at the global scale (Rosenzweig et al., 2014). As other process-based models, they conceptually represent soil-plant-atmosphere biophysical processes, their interactions and feedbacks. The processes are quantitatively expressed through mathematical functions and their effects are integrated over time steps, so that the temporal dynamic of e.g. crop growth is explicitly simulated. Different crop species are represented though specific sets of processes, parameters or functions, which are typically derived on experimental bases (Jones et al., 2017; Muller and Martre, 2019b). In the GGCMs, inputs and outputs are grid-based and have both spatial (longitude, latitude) and temporal (days, years) dimensions. Inputs include atmospheric CO_2, climate, soil and agronomic management data. They estimate simultaneously multiple crop-specific variables, including yields, biomass production, maturity dates, and cumulative evapotranspiration.

All simulations were run at 0.5 degree spatial resolution and for 31 years of the historical climate (1980-2010); models with a daily time step used AgMERRA climate data (Ruane, Goldberg, and Chryssanthacopoulos, 2015), while those with subdaily temporal resolution used ERA-Interim (ERA-I) (Dee et al., 2011). We assume that the use of two different climate products does not affect the analysis much, as both datasets are observation based and were treated with the same perturbation approach (see below). Current cropland patterns were selected in model post-processing. The grid cell- and crop-specific area was obtained from MIRCA2000 (Portmann, Siebert, and Döll, 2010) dataset at 0.5 degree resolution. The experiment design consisted of separate simulations for five crops (maize, rice, soybean, spring wheat, winter wheat), under one baseline temperature scenario (T0) and five levels of globally uniform temperature increases (T1, T2, T3, T4, T6). Moreover, four management settings were simulated, that we call *control management* setting (*T-sensitive growing period* & *Rainfed*) and three *adaptive management* setting (*Fixed growing period* & *Rainfed*; *T-sensitive growing period* & *Irrigation*; *Fixed growing period* & *Irrigation*). To target specific adaptation strategies it is necessary to isolate the effect of individual climatic factors, as there is uncertainty in e.g. the temperature sensitivity to increased CO_2 and in future correlations between precipitation and temperature patterns (Carter et al., 2016; Zhao et al., 2017; Schleussner et al., 2018). In this study we aimed at isolating the impact of adaptation

[1]Supplementary Information for this chapter are reported in Appendix A of the thesis.

Table 2.1: GGCMs participating in the study with main references.

GGCM	References
CARAIB	Dury et al. (2011b); Pirttioja et al. (2015)
GEPIC	Liu et al. (2007) and Folberth et al. (2012)
LPJ-GUESS	Lindeskog et al. (2013) and Olin et al. (2015)
LPJmL	von Bloh et al. (2018)
pDSSAT	Elliott et al. (2013) and Jones et al. (2003)
PEPIC	Liu et al. (2016b)a; Liu et al. (2016c)b
PROMET	Mauser and Bach (2009), Hank, Bach, and Mauser (2015), and Mauser et al. (2015)

of crops and agricultural management to temperature increase. Therefore, the atmospheric CO_2 mixing ratio was kept constant at 360 ppmv in all simulation years and scenarios (see Discussion). To verify whether our conclusions are independent from the CO_2 mixing ratio, we repeated the experiment also at 660 ppmv. For the comparison, we rely on a smaller set of GGCM, because GEPIC and PEPIC did not provide the full CO_2 offsets simulations (Fig. S15). Similarly, precipitation and other climate drivers were unchanged across scenarios. The five artificial warming scenarios were created by perturbing input daily air temperature by five respective offsets (+1, +2, +3, +4, +6 K).

The model ensemble was harmonized for three key management practices: 1) the growing period; 2) the water supply (rainfed or fully irrigated); 3) the nitrogen-fertilizer application rate (assumed to be 200 kgN ha^{-1} y^{-1} uniformly for each crop and cropping season, applied in two doses: 50% at planting, 50% on a crop- and grid-specific day (see protocol in SI, section 1.1). The growing period harmonization followed the protocol of GGCMI phase 1 (Elliott et al., 2015), based on observed growing period data (Sacks et al., 2010; Portmann, Siebert, and Döll, 2010), gap-filled with rule-based (Waha et al., 2012) cropping calendars. Modellers were asked to calibrate the phenology, so that the average (over the 31-years simulation period) growing periods matched the provided crop- and grid-specific sowing and maturity dates. Sowing dates were kept constant at the historical observations. Maturity dates were estimated from observed harvest dates by subtracting crop-specific maturity-to-harvest times (21, 7, 21, 7, 7 days for maize, rice, soybean, spring wheat, winter wheat respectively) from the latter (Elliott et al., 2015). The procedure for the calibration to observed growing periods was individually chosen by each modeling team, which could freely determine phenological parameters such as cardinal temperatures, growing degree days, vernalization and/or photoperiod requirements, as well as set these as grid-specific or as global values. The obtained parametrization was assumed to describe the available historical crop cultivar pool, see details in Table 2.2 and Table S1.

In addition to simulations assuming *control management*, three *adaptive management* scenarios were simulated for each temperature level. Under the *fixed growing period* setting we assumed the use of different hypothetical cultivars with adapted phenological traits, which maintain the reference growing period under each warming level. This represents a measure to counteract the higher-temperature effect on the phenological development rate,

Table 2.2: GGCMs participating in the study with main features of their phenological module. More details are reported in Appendix (Section 1.2 and Table S1).

GGCM	Temperature response function	Phenological drivers	Perceived Temperature	Phenological phases
CARAIB	Lin., Tmin	T(GDD), W	Tair	1 (S-M)
GEPIC	Lin., Tmin, Topt	T(GDD), T(V), DL	Tair	1 (S-M)
LPJ-GUESS	Lin., Tmin, Topt*, Tmax*	T(GDD), T(V)	Tair	2 (S-A-M)
LPJmL	Lin., Tmin	T(GDD), T(V)	Tair	1 (S-M)
pDSSAT	Lin., Tmin, Topt	T(GDD), T(V), DL, W	Tair	crop-specific
PEPIC	Lin., Tmin, Topt	T(GDD), T(V), DL	Tair	1 (S-M)
PROMET	Curv., Tmin, Topt, Tmax	T(DVR), T(V), DL, W	Tleaf	100 (BBCH)

Temperature response function for phenology Wang et al., 2017: Lin, linear; Curv., curvilinear; Tmin; minimum cardinal temperature; Topt, optimum cardinal temperature; Tmax, maximum cardinal temperature; * for spring wheat and winter wheat only.

Phenological drivers: T(GDD), temperature (growing degree days); T(DVR), temperature (development rate); T(V), temperature (vernalization); DL, daylength; W, water; N, nitrogen.

Perceived temperature: Temperature perceived by the crop, driving phenological and metabolic processes (Tair, air temperature; Tleaf, leaf temperature).

Phenological phases: S, sowing; A, anthesis; M, maturity; BBCH, full BBCH.

by which the time between sowing and maturity is generally shortened. All GGCMs use thermal time as the main driver of phenological progress (Table 2.2), therefore higher air temperature offsets are expected to affect the growing period durations. The *fixed growing period* implementation was simulated by adjusting the crop phenological parameters, so that the average (over the 31-years simulation period) length of the growing period (in days) was the same (as closely as possible) under all T0-T6 scenarios. Therefore, modellers were asked to implement individual solutions to maintain the 1980-2010 mean growing period extent (e.g. precalculating changes in thermal time requirements based on fixed temperature shifts or adjusting by iteration). For models that separate phenology into multiple stages (e.g. sowing-to-anthesis and anthesis-to-maturity) modelers were asked to scale parameters of each stage equally, so that the timing of intermediate stages such as anthesis stayed approximately the same. Under the *irrigation* setting we assumed the supply of unlimited irrigation water to the crops. Irrigation is studied as an adaptation measure to temperature increase because there are interactions between crop temperature and water supply. Higher air temperatures can increase the rates of evapotranspiration and soil water depletion, while soil water deficits can reduce evapotranspiration and thus increase the canopy temperature, consequently affecting the phenological development and growth rates. Although not all these effects are included in the GGCMs, each of them represents water to temperature interaction in some ways. All the ensemble's GGCMs simulate evapotranspiration by formulas that require temperature as an input variable, thus temperature increases are expected to modify the crop water demand. Moreover, some GGCMs represent the feedback between water stress and phenology. Particularly, two models include water deficit as directly affecting phenological progress (Table 2.2). In pDSSAT water deficit may delay the onset of reproductive growth, while it accelerates the grain filling phase (Jones et al., 2003), while in CARAIB the water deficit may delay germination. Only the PROMET model includes the indirect effect of soil water status on phenology, through the explicit simulation of the leaves temperature (Table 2.2). Water deficit results in increased leaf temperature, that usually accelerates the phenological progress. Irrigation was assumed to be unconstrained by surface water availability. *Irrigation* was implemented to re-fill soil water content to field capacity as soon as it fell below a threshold of 90% of field capacity (Elliott et al., 2015). We also tested the combination of *fixed growing period* and *irrigation*.

2.2.2 Model output processing

Models reported yearly dry-matter yields (Mg ha^{-1}), sowing dates (day of year, DOY), maturity-dates (days from planting) for the period 1980-2010, separately for maize, rice, soybean, spring wheat and winter wheat. Yield failures were reported as 0 Mg ha^{-1}, while non-simulated grids were reported as NA values. Maturity dates of yield failure years were set to NA.
We computed the long-term averages (1981-2009) for yield, sowing date and maturity date for the period 1981-2009 for each model, temperature offset scenario, and management setting, respectively. The first and last year of the simulation time series were excluded to avoid reporting issues relating to completeness of growing periods (Elliott et al., 2015).

Under the reference temperature scenario ($T0$) the growing periods were assumed to be the same in all management settings, and thus yields were assumed to be the same as well for the *rainfed* and *irrigation* settings respectively. For efficiency reasons, outputs for $T5$ were not simulated, but derived by linear interpolation between $T4$ and $T6$ for each GGCM, crop and grid cell, independently for each of the management setting (categorical variables). Some individual simulations were not available for all models (Fig. S1), and we gap-filled missing simulations by linear interpolation of neighboring scenarios (with an exception for rice and soybean for the LPJ-GUESS model that were not simulated at all, and for winter wheat for the PEPIC model that was excluded from the analysis due to unreliable simulations of the growing periods). The CARAIB model had only sowing dates harmonized, while the model was not calibrated to match observed harvest dates (see Section 1.2.1 for details), but the simulation with *fixed growing periods* are unaffected.

All GGCM output data are made publicly available at zenodo.org repository. The DOI references are provided in Table 2.3. For data processing we used R (R Core Team, 2018), and R-packages for handling netcdf4 (Pierce, 2015), performing computation (Dowle and Srinivasan, 2017; Wickham, 2011) and plotting results (Wickham, 2009).

2.2.3 Metrics

All GGCMs included in this study simulate crop phenology as a function of temperature (thermal-unit sum, vernalization). We quantified the average impact of globally uniform temperature increase on growing periods and yields across all GGCMs and cropland grid cells by fitting linear regression models for each individual crop (Fig. 2.2a,b). To understand

Table 2.3: DOI references for accessing the data used in this study. All GGCMs' output data, separated by crop and model, can be found at https://doi.org/10.5281/zenodo/XX, where XX is the value reported in the table.

GGCM	Maize	Soybean	Rice	Winter wheat	Spring wheat
CARAIB	2582522	2582508	2582504	2582516	2582499
GEPIC	2582247	2582258	2582251	2582260	2582263
LPJ-GUESS	2581625	–	–	2581638	2581640
LPJmL	2581356	2581498	2581436	2581565	2581606
pDSSAT	2582111	2582147	2582127	2582163	2582178
PEPIC	2582341	2582433	2582343	2582439	2582455
PROMET	2582467	2582488	2582479	2582490	2582492

whether there is a direct relationship between responses of growing periods and yields to temperature increase, we analyzed the joint distribution of their changes from the reference scenario (T0). We categorized the possible responses into four classes, defined by the sign of change of the two variables, and illustrated their frequency of occurrence within each class and climatic regions (Fig. 2.2c).

To quantify the impact of temperature increase on global production of all crops, we estimated the production change (%) under warming scenarios as compared to the reference temperature scenario (T0). Since here we considered production of crops of relevance for human nutrition, we transform yields from metric tons to their calorie content, as this is the most common metric for quantifying globally available food (Willett et al., 2019). The grid-based global calories production under the management system m and temperature offset n ($P_{m,n}$, Eq. 2.1) was obtained as the sum of production across all crops (c) and grid cells (g). Within the grid cell j, the yield of crop i was multiplied by its calorie content and by its area in that grid.

$$P_{m,n} = \sum_{j=1}^{g} \sum_{i=1}^{c} area_{j,i} \cdot yield_{j,i} \cdot calorie_i \tag{2.1}$$

The calorie content values were derived from the FAO food balance sheet handbook (Food and Agriculture Organization, 2001), which reports food composition in terms of weight "as purchased", therefore model output yields were converted from dry- to fresh-matter as from Wirsenius (2000) to obtain the calorie-yield per crop and unit of area (Table 2.4).

To determine whether the simulated adaptation measures are effective, we computed the *Adaptation Index* (AI, Eq. 2.2) (modified from Lobell (2014)) for each grid cell, temperature offset, and *adaptive management* setting as

$$AI = 100 \cdot (c - b)/|a|,\ if\ a < 0 \tag{2.2}$$

where a is the impact of temperature increase on yield under *control management*, b is the effect that the *adaptive management* would have under the reference scenario T0, c is the effect of the *adaptive management* under increased temperature scenarios (Fig. 2.1).

Table 2.4: Crop-specific parameters used for converting the crop yield model outputs from metric tons of dry matter (Mg ha^{-1}) to their calorie content (Gcal ha^{-1}). The grain dry matter (% of as-purchased grain weight) is the yield conversion factor between as-purchased-grain weight and dry-grain weight. The calorie content are the calories per metric ton of as-purchased grain weight.

Crop	Grain dry matter (% as-purchased)	Calorie content (Gcal Mg^{-1})
Maize	88	3.560
Soybean	91	3.350
Spring wheat	88	3.340
Winter wheat	88	3.340
Rice	87	2.800

Note that by definition under T0 the *fixed growing period* is equal to *T-sensitive growing period* and therefore b is zero for this *adaptive management* scenario. Values of AI are computed only if a is negative, otherwise temperature increase is considered beneficial. AI ranges between $-\infty$ and $+\infty$, with $AI \geq 100$ indicating full- or over-compensation of losses (full adaptation); $0 < AI < 100$ indicating partial-compensation of losses (partial adaptation); $AI < 0$ indicating no-compensation of losses, meaning either an amplification of damages or that the *adaptive management* can be increasing production, without being impact-reducing (intensification), and therefore not a true adaptation measure (Lobell, 2014). AI was computed for each single GGCM and we then computed the median ensemble and uncertainty (range) across GGCMs.

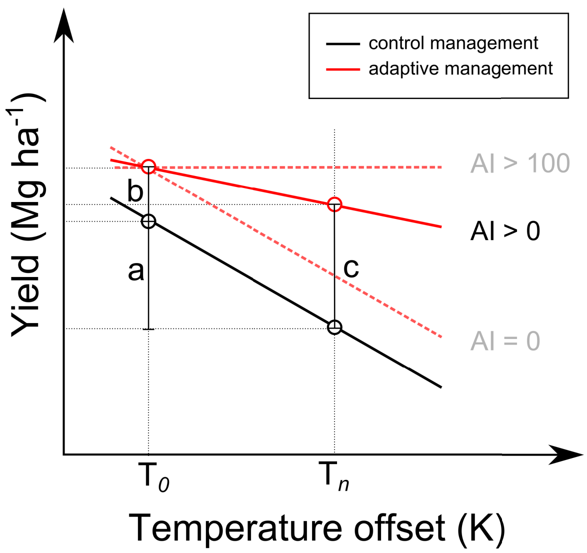


Figure 2.1: Diagram of the Adaptation Index (AI) computation (Modified from Lobell (2014)). The plot shows the yield (Mg ha^{-1}) as a function of increasing temperature between the reference climate and the offset temperature T_n (ranging from T1 to T6). The black and the red lines represent the Yield$\sim$Temperature response with *control* and *adaptive* crop management, respectively. The red dashed lines delimit the space where *adaptive* management only partially compensate yield losses ($0 < AI < 100$). AI is computed as in Eq. 2.2 where a is the yield impact of the temperature increase from T_0 to T_n on yield under *control* management, b is the effect that the adaptive management would have under the reference conditions (T_0), c is the effect of the *adaptive* management under the offset temperature T_n.

2.3 Results

2.3.1 Crop phenology response to temperature offsets without adaptation

At the global aggregation level, in absence of adaptation measures, the growing period length approximates a negative linear response to increasing temperature from 1 to 6 K (Fig. 2.2). The slope of this relationship (days of growing period lost per Kelvin of warming) is similar across the five simulated crops, ranging from 5.4 $days\,K^{-1}$ (maize) to 3.8 $days\,K^{-1}$ (spring wheat). The spread of growing period length across all GGCMs and all cropland globally does not change fundamentally at higher temperature offsets (whiskers in Fig. 2.2), yet it somewhat increases for soybean, and decreases for winter wheat. The general response is similar across the GGCMs as most models simulate shortening growing periods with higher temperatures (Fig. S4). Yet, some models show smaller sensitivity of the growing period change across crops (PEPIC and PROMET), and in one case an opposite sign of change (rice for PROMET). In PROMET phenology is implemented to slow down at high temperatures above a crop-specific optimum (Table 2.2), so that warming can also lead to growing periods longer than in the reference temperature scenario. This is the case for LPJ-GUESS (spring and winter wheat) as well, although parametrized with higher optimum thresholds (Table 2.2), which could be the reason for the non occurrence of such increase. In some GGCMs (LPJmL, PROMET), for winter wheat, vernalization requirements are not satisfied as quickly under warming, so that the phenological development decelerates. Spatial patterns of growing period length at different temperature levels show that its shortening (days) is especially pronounced in cold-temperature limited regions for maize and soybean (Fig. S8a), because under warming more days reach temperatures above the crop-specific base temperatures (T_{min}).

2.3.2 Impact of temperature offsets on crop yield

The crop yield response follows similar patterns as the growing period, with an almost linear decline with temperature at the global aggregation level. Yield declines range between 0.36 $Mg\,ha^{-1}\,K^{-1}$ for rice and 0.11 $Mg\,ha^{-1}\,K^{-1}$ for winter wheat (Fig. 2.2b). As opposed to the growing period length, the spread of the GGCMs declines with higher temperature offsets. For rice, soybean and winter wheat, we also observe narrowing interquartile ranges (Fig. 2b) with higher temperature offsets. This reflects a stronger reduction of high yields than of low yields. Indeed, for some regions and models yields are already null under the baseline climate, and cannot decrease further.

Changes in growing period and changes in crop yields do not follow a one-to-one relationship, but in most cases (~69% of all cultivated grid cells, across crops and temperature offsets) shorter growing periods are associated with declining yields (Fig. 2.2c, S8): 69, 61, 68, 69, and 11 % for tropical, arid, temperate, continental and polar areas respectively. There are rare cases where decreasing growing periods are associated with increasing yields or where longer growing periods are associated with declining yields. The former can be explained by either the beneficial effect of overall higher growing season temperatures that stimulate primary productivity, as for maize in high latitudes, or by the benefit of a shorter growing

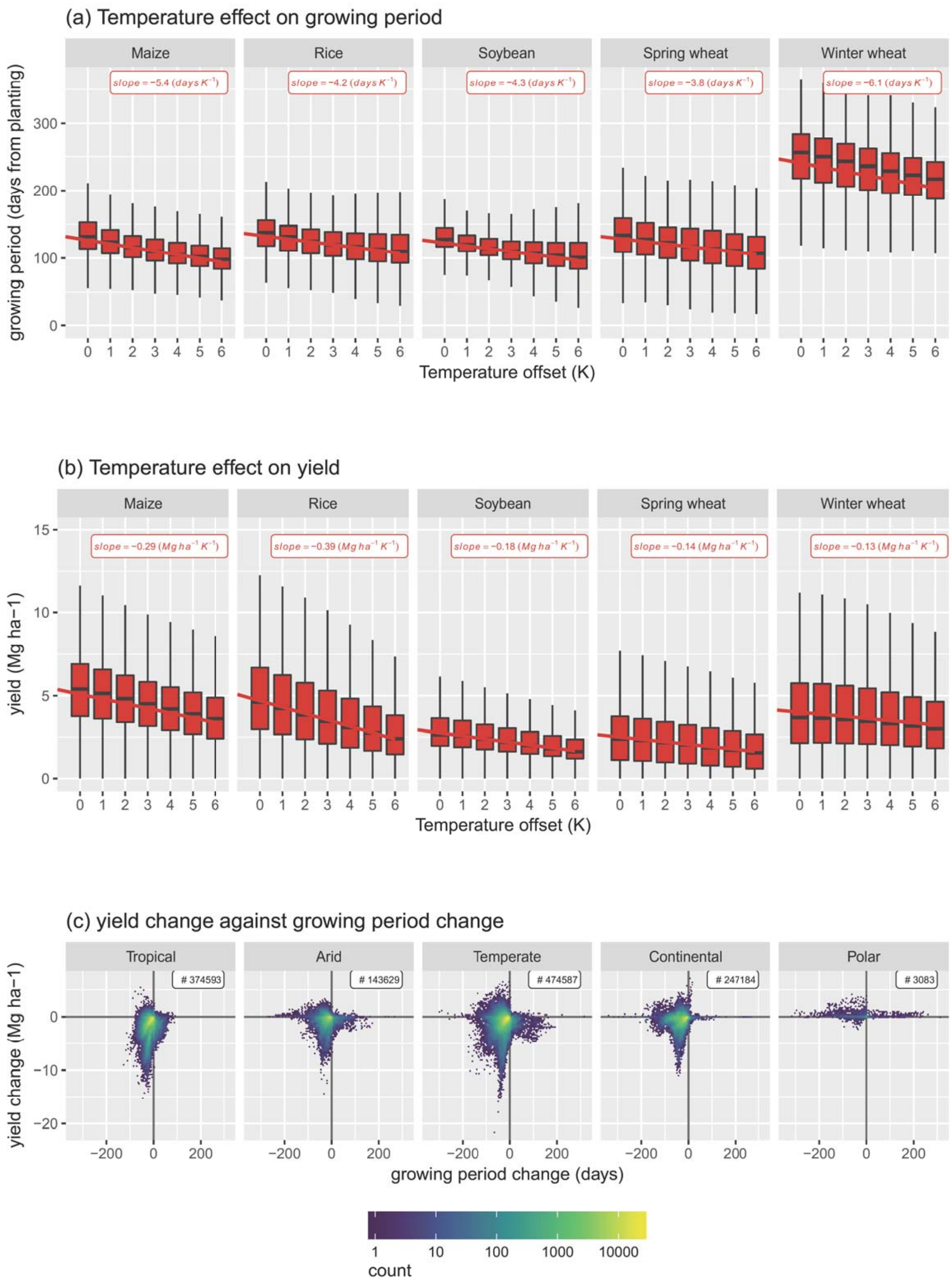


Figure 2.2: Effect of increasing temperature on crop phenology (growing period duration, days from planting) (a) and yield (Mg ha^{-1}) (b), separated by the five simulated main staple crops, without any adaptation measure. Each box represents the the 25th, 50th, and 75th percentile of all grid cells values of all GGCMs for a specific temperature offset. The whiskers extends from the hinge to the smallest and largest values respectively, no further than 1.5 interquartile range. The red line is the linear regression across simulated values and temperature offsets and its slope is indicated in each plot. The heat map in panel (c) displays the relationship between yield changes (Mg ha^{-1}) and growing period changes (number of days) for all crops and all temperature offsets, separated by the Koeppen-Geiger climate regions. Changes are calculated as the absolute differences between the reference and the offset scenario. Plot in (a) and (b) includes all cultivated grid cells at all temperature offsets between T1 and T6; note that T5 is not simulated but linearly interpolated from T4 and T6. T5 is not included in (c). Hexagons are colored according to their frequency count.

season that escapes water stress, if water conditions become more limiting under increased temperatures. Similarly, longer growing periods can lead to yield decline if the growing periods extend into dry season. Longer growing periods with increasing crop yields are, however, basically non-existent.

2.3.3 Effectiveness of adaptation measures

Increasing temperatures decrease global production of all crops almost linearly, except for winter wheat, where decrease only starts at a warming of ∼2 K (red line in Fig. 2.3a). Using different cultivars, so that the original growing period would be maintained, the total global calorie production of all five crops can be stabilized up to ∼2 K and declines with further warming (*fixed growing period* setting; yellow lines in Fig. 2.3a; all crops). Individual crops, however, show different temperature responses. Rice, soybean and spring wheat show an almost linear decline with any warming. For maize, the *fixed growing period* setting leads to stable global production up to warming of ∼3 K. For winter wheat, warming of up to ∼4 K is projected to even increase global production and decreases only thereafter. At the global aggregation level the agreement across GGCMs is reasonable, except for large uncertainty for spring wheat (yellow shaded area in Fig. 2.3a). All models show benefits from the *fixed growing period* setting, compared to *control management*. For all crops except rice, there is always at least one GGCM that simulates increase global production with the fixed growing period setting up to > 5 K.

Converting all currently rainfed to irrigated cropland (assuming unlimited water supply; *irrigation* setting) would increase global calorie production by ∼20% (blue line in Fig. 2.3a). At such higher level, fully-irrigated production would also decline with increasing temperatures at similar rates to rainfed production. Yet, the intensification through irrigation could maintain current production levels up to ∼4 K at global level across crops. Similar patterns are displayed by all crops, while irrigated winter wheat may be able to maintain current production levels even up to > 6 K. In combination, the *fixed growing period* and *irrigation* measures support global calorie production increases up to 4 K temperature offests (green line in Fig. 2.3a) and could maintain current levels across all tested warming levels. For maize, the combined implementation of both measures leads to continuous increases in production across all tested warming levels. Global rice production seems to be least sensitive to the two adaptation options at any temperature offset. Across the different GGCMs, the effects of irrigation on currently rainfed cropland are generally more uncertain than the effects of warming on rainfed crop production. The size of the response of spring wheat production to introducing *irrigation* to all rainfed areas is highly uncertain across GGCMs, as two models (LPJmL and pDSSAT) project roughly doubled spring wheat production under irrigation, whereas the other models project increases of only 25%. Still, as for the other crops, the uniform decline of irrigated spring wheat production is found by all GGCMs.

The level of warming up to which global production of all crops can increase differs across regions and management scenarios (Fig. 2.3b). Particularly, in the tropics under the *fixed growing period* global rainfed production is already declining at 1 K of warming, whereas in temperate and continental zones it increases up to high levels of warming (also 6 K). *Irrigation* would maintain higher production levels up to 6 K in arid regions, where however

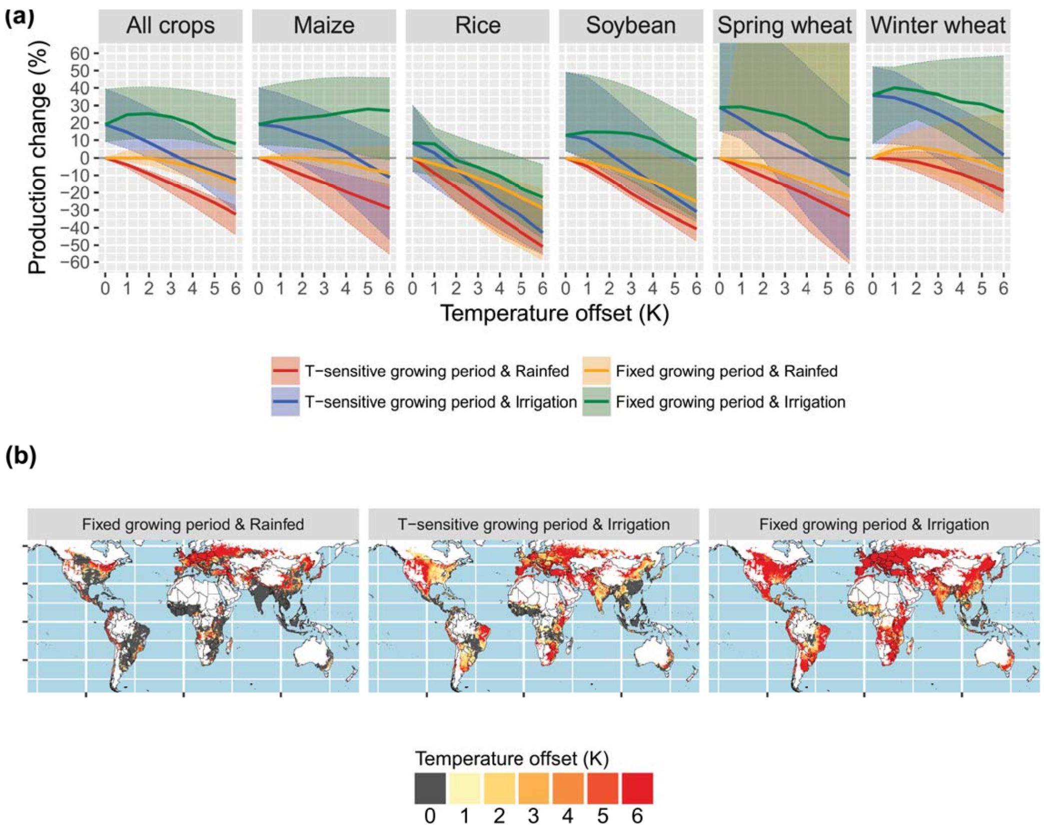


Figure 2.3: Effect of increasing temperatures and four management settings on global calorie production. (a) Calories production change (percent change), shown as an aggregation for each crop. The lines and the shaded areas represent the median and the range of the GGCM ensemble respectively. For visualizing the full range of the spring wheat crop, refer to Fig. S11. (b) Global patterns of temperature offsets up to which calories production of all crops increases under each *adaptive management* scenario, compared to the *control management* in the baseline temperature scenario (T0).

irrigation expansion would be difficult due to the scarce water resources. In temperate and tropical regions where *irrigation* would likely be more feasible, this measure is effective until moderate warming only, or not effective at all like in many tropical areas. Only the combination of *fixed growing period* and *irrigation* maintains crop production above the original level in largest part of the global land. Yet, the tropical areas show production declines at 1 to 4 K of warming.

Increases in crop production are in some cases also a direct effect of temperature increase, even in absence of management changes, as in in high-latitude regions (dark green in Fig. 2.4a). Although the three management options show potentials to increase crop productivity globally, they are not necessarily true adaptation measures. Particularly, we find that despite the positive effect of *irrigation* in leverage yields, it does not ($AI < 0$) or only partially ($0 < AI < 100$) reduce the negative effect of warming (shortening of the growing period), but rather overcompensate them. The effectiveness of the *fixed growing period* differs across regions (Fig. 2.4a). Fig. 2.4a shows in detail the effectiveness of the *fixed growing period* adaptation for a warming level of 4 K, however, the patterns are very similar across all warming levels tested here (see Fig. S13). In temperate and continental regions, there is larger potential for adaptation through the *fixed growing period* than in tropical and arid regions. The *fixed growing periods* measure has hardly any positive effect in arid regions, but has the potential to maintain current production levels in continental regions (see Fig. S12). In arid regions, the *fixed growing period* measure can lead to amplified damages and would thus be a form of "maladaptation" (orange color in Fig. 2.4a, S13, S14). The models here capture the typical interaction mechanism between plant phenology and water use. The selection of earlier-maturing cultivars in environments characterized by water shortage is a well-known strategy for avoiding water stress to crops (Bodner, Nakhforoosh, and Kaul, 2015). Under increasing temperatures, the atmospheric water demand increases as well, which cannot be fulfilled by actual evapotranspiration. Extending the growing period therefore worsens water stress, determining a maladaptation effect. There are substantial differences in the global patterns of adaptation effectiveness across the GGCMs (Fig. 2.4b, Fig. S13), with a larger agreement on where *fixed growing period* has little adaptation effectiveness, but models often disagree (larger ensemble AI range) on the magnitudes of the adaptation effectiveness of the *fixed growing period* measure (Fig. 2.4b).

In tropical regions, *irrigation* has little potential to intensify production, whereas it has substantial potential in arid regions with highest levels of water stress (see Fig. S12). However, availability to realize these potentials are not considered here.

Under higher CO_2 mixing ratio of 660 ppmv, temperature impacts with the *control management* are slightly reduced compared to those under 360 ppmv. However, the findings on *fixed growing period* and *irrigation* adaptation potentials, hold valid also when assuming higher CO_2 mixing ratio (Fig. S16, S17, S18). For spring wheat only the adaptation potential of the *fixed growing period* setting is larger under 660 ppmv than at 360 ppmv, so that global level production can be maintained across all temperature offsets.

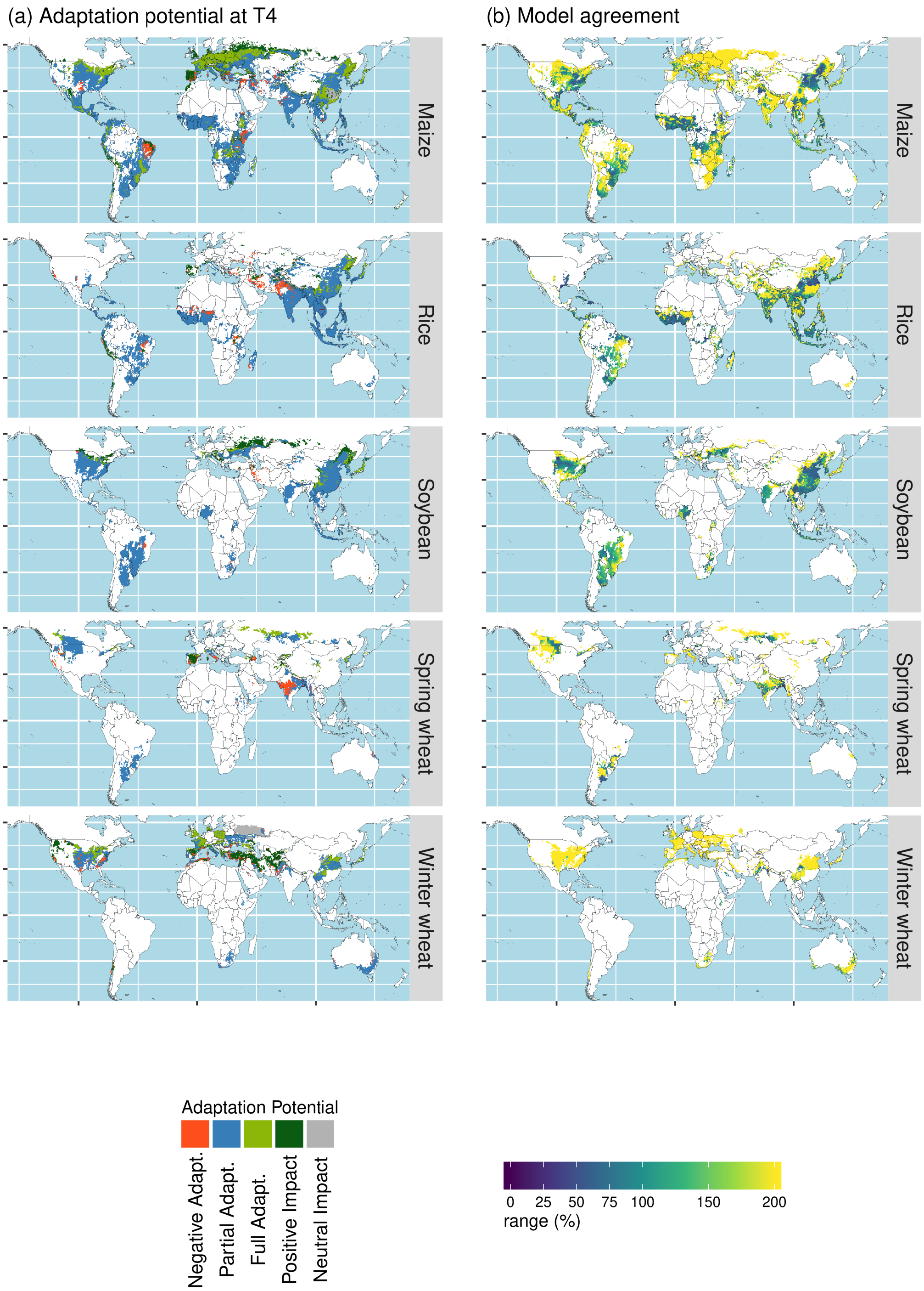


Figure 2.4: Adaptation potential of rainfed crops under a 4 K temperature offset in combination with *fixed growing period* adaptation scenario (a), and model agreement (b). Panel (a) shows GGCM ensemble medians for: (i) negative temperature impact and negative adaptation effect (orange, $a < 0$ & $AI < 0$); (ii) negative temperature impact and positive adaptation effect, but with only partial compensations (blue, $a < 0$ & $0 < AI < 100$); (iii) negative temperature impact and positive adaptation effect, with full compensation (light green, $a < 0$ & $AI > 100$); (iv) positive temperature impacts (dark green, $a > 0$); (v) neutral impacts (gray, $a = 0$). Panel (b) shows the range of AI across GGCMs, only in the grid cells where temperature increase has negative impacts ($a < 0$). Values larger than 200% are constrained to 200% for better visualization. AI and a are computed as in Eq. 2.2.

2.4 Discussion

Using a large ensemble of GGCMs in a systematic warming experiment, we find that temperature increases lead to continuous reductions in global crop production without compensating adaptation measures, which is in line with previous findings (Challinor et al., 2014; Rosenzweig et al., 2014; Lobell, Schlenker, and Costa-Roberts, 2011; Liu et al., 2016a; Zhao et al., 2017). Our results suggest that this decline is driven by a combination of accelerated phenology and thus shorter growing periods as well as by direct effects on plant growth. As such, selecting cultivars that maintain the original growing period under warming is a viable adaptation measure in most regions, as it reduces or fully compensates negative effects of warming on crop yields. This confirms recent findings in that historical warming already leads to the use of longer maturing cultivars, which in turn contributed to the increasing yield trend in the United States and Europe (Butler, Mueller, and Huybers, 2018; Parent et al., 2018). The response, however, is variable across regions, crops and GGCMs and thus subject to uncertainties.

In absence of detailed information on crop and cultivar parameters, process-based models applied at global scale have to make critical assumptions. Folberth et al. (2016) highlights how important the assumptions on management aspects are for simulating crop yields. Simulated adaptation potentials at global scale are neccessarily affected by coarse model assumptions as well. Previous GGCMI ensemble studies show that harmonization of management settings (Elliott et al., 2015) can have substantial effects on model performance (Müller et al., 2017), however, only a small set of settings can be harmonized, limited by the availability of global data sets (e.g. fertilizer, growing periods). Recently, Jägermeyr and Frieler (2018) highlighted that the correct timing of the growing season is particularly critical for realistic yield simulation. In this exercise, participating modelers are therefore asked to parametrize crop phenology so that current observed growing periods (Elliott et al., 2015) are reproduced by each model (by calculating required thermal-units based on AgMERRA weather data, (Ruane, Goldberg, and Chryssanthacopoulos, 2015)). In the simulations without *fixed growing period* adaptation (*T-sensitive growing period* setting), simulated growing periods are allowed to respond to warming, depending on the individual GGCMs' implementation of phenology (Table 2.2). In the *fixed growing period* adaptation setting, the crop phenology parameters were re-calibrated for each warming level, so that the growing period length was roughly unaffected. However, no harmonization was requested for any other cultivar parameters or the functional form of the phenological response to temperature (Table 2.2). To this end, the ensemble of GGCMs used here reflects a broader variety of cultivars and management systems, which may explain part of the diverse modeled regional response to *fixed growing period* adaptation. Cardinal temperatures of phenological development (Table S1) are considered crop specific (Hatfield et al., 2011b), with very little variability within species among genotypes and no acclimation to changes in temperature (Parent and Tardieu, 2012), therefore supporting the use by the GGCMs of crop-specific global parameters in the temperature response function for phenology. On the other hand, photosynthesis and enzyme activity acclimate to higher temperature (Parent and Tardieu, 2012) and cultivars differ in their sensitivity to heat stress. In particular, cultivars that are selected in hot climates are less sensitive to yield losses (Butler and Huybers, 2013), a feature that is not reflected in the GGCMs. Rezaei et al. (2018) suggest that the temperature response in phenology could be flawed by not accounting for changes in cultivar choice in the historic past. Also Zhu et al. (2019) find that GGCMs often overestimate the response in growing period length compared to other yield-reducing effects of warming. This uncertainty in regional responses is in contrast to the robust finding of *fixed growing period* adaptation at the global aggregation, where models do not differ much. It remains unclear how the diverse regional responses need to be aggregated. Considering the complex interaction of initial cultivar parameterization for baseline yields and warming effects (Folberth et al., 2016) this requires further research and requires better information on existing management systems globally. In this study we assume the availability of the adapted cultivars to maintain the growing periods. However it is not clear whether these would actually be available today or in the future, and how large would the effort be for breeding such new cultivars, especially under elevated temperatures (Challinor et al., 2016).

While irrigation comes with substantial potential to lift yields in water-limited regions, therefore buffering temperature-induced adverse effects, converting rainfed to irrigated crop production cannot be considered as a true adaptation measure, but rather intensification Lobell (2014). This is because the beneficial effect of irrigation is similar under warming and under current conditions. This is surprising, because previous studies suggest that irrigation reduces the direct negative effects of warming on crop yields. Schauberger et al. (2017) find that irrigation buffers against damages from exposure to hot temperatures for maize in the USA and maize yield response to temperature is found to be highly leveraged by soil moisture status (Carter et al., 2016) and thus presumably irrigation in dryer areas. Observed yield declines during historical heat waves and droughts are predominantly attributed to rainfed systems (Jägermeyr and Frieler, 2018). The lack of reproducing this effect in this model ensemble may be due to several reasons. First, only one of the seven GGCMs (PROMET) accounts for the cooling effect of increased transpiration under irrigation by simulating canopy temperature, whereas all other models assume canopy temperature to be equal to air temperature. However, PROMET also shows the same pattern in the response to irrigation and warming as all the other GGCMs: intensification of production through converting rainfed to irrigated production, but no benefit on the negative response to warming (see Fig. S11). Second, if models tend to overestimate the growing period response to warming, as suggested by Rezaei et al. (2018) and Zhu et al. (2019), it may be that the shortening of the growing season overly dominates the yield response and direct effects of warming on plant growth are underrepresented in the current GGCMs. If canopy temperatures are not accounted for, irrigation cannot affect the simulated length of the growing period and will not show the underrepresented effects on crop growth. Nonetheless this intensification could compensate for much of the warming-induced damage, at least in regions where irrigation water could be supplied.

We find that the challenge to maintain current productivity levels under warming is particularly large in the tropical and arid climate zones, given that the adaptation of *fixed growing period* has little potential to reduce the negative effects of warming on crop yields and that shifting rainfed to irrigated production has little potential in the tropics and will be severely hampered by water availability in most arid regions. Furthermore, large areas of the tropics are bound to experience climate conditions that have no analogues under current climate conditions (Pugh et al., 2016), so that breeding or designing cultivars for such conditions will be particularly challenging.

Generally, the GGCMI phase 2 modeling experiment is an artificial setup with several implications for the interpretation of results (Supporting Information 1.1). First, we study the effects of warming in a uniform manner, i.e. all days warmed by exactly the same offset, which is not representative for realistic climate change scenarios. Second, associated impacts from changes in precipitation under climate change are ignored, while direct impacts of elevated atmospheric CO_2 mixing ratios are tested in a rather simplistic manner. This can substantially enhance crop growth (Kimball, 2016), but also amplify high temperature damage to crops (Prasad, Boote, and Allen Jr, 2006). However we find that our findings regarding adaptation potential to temperature increase remain valid under both CO_2 mixing ratios. Third, we here consider only high-input systems with nitrogen fertilization levels of 200 kgN ha^{-1} and no other nutrient limitations (e.g. Phosphorus, Potassium). However, these simplifications seem justified, as we are aiming to understand how warming-induced damages to crop production can be compensated by an adaptation measure that counteracts the phenological acceleration, which is almost exclusively temperature driven. This sensitivity study helps to isolate effects, which are typically difficult to separate in realistic climate scenarios, in which the relationship of changes in temperature, precipitation and atmospheric CO_2 mixing ratios are very model dependent (McSweeney and Jones, 2016). Nevertheless, results from the GGCMI CTWN-A experiment as analyzed here should not be misinterpreted as assessments of adaptation options under realistic climate change scenarios.

The adaptation measure to regain the warming-induced loss of growing period duration considered here is also a simplified theoretical case. As the maintaining of the original growing period is not always beneficial or somewhat shorter or longer growing periods could have even greater potential to adapt to warming, this only represents one specific case of a broader continuum. Also, adaptation in cultivar choice is likely linked to changes in sowing dates to best adapt cropping systems and exploit benefits of a longer growing season, as it is already observed with already contributes to recent yield trends (Butler, Mueller, and Huybers, 2018; Parent et al., 2018). Flexible sowing dates could thus further increase the adaptation potentials shown here as we assume static sowing dates even under extreme temperature offsets. This is especially relevant in regions with temperature seasonality (Waha et al., 2012). Shifting sowing dates has nonetheless its complications, especially for crops with sensitivity to photoperiod and or vernalization, as it could in turn affect the length of the growing period, with importance consequences on the final yields (Abdulai et al., 2012; Hunt et al., 2019). Moreover, we analyze winter and spring wheat separately, therefore maintaining their crop areas static as though they were two different crops. This is a simplification, as these are rather two varieties of the same species, of which the spatial distribution depends on temperature, and particularly on the existence of a winter season suitable for vernalization. A change in temperature level can then make it more advantageous to switch between winter-and spring-varieties, than trying to maintain the original growing season as an adaptation option. However, selecting a static growing season as a uniform adaptation measure again facilitates better interpretation of the results. Still, uncertainties are linked to the differences in interpreting the modeling protocol. The simulations conducted by CARAIB did not parametrize cultivar traits to reproduce the harmonization target for crop maturity (Elliott et al., 2015), but do keep their growing seasons constant under warming in the adaptation setup. Other models did follow the harmonization protocol, but growing seasons are not always closely reproduced (see Fig. S2). This contributes to the uncertainty in the modeled response to adaptation.

2.5 Conclusions

Without agronomic adaptation measures, future warming as projected under climate change will negatively affect global crop production in absence of adaptation measures. Despite possibly compensating or amplifying effects form simultaneously changing precipitation and atmospheric CO_2 concentrations, it is important to understand temperature driven plant physiological processes, in order to identify which adaptation options to warming-induced yield reductions. By using a global gridded crop model ensemble, we find that adaptation via new cultivars that would maintain current crop growing periods under warming is a viable option with substantial potential to fully compensate warming-induced yield reductions, especially in the temperate and continental climate zones. Even though growing period adaptation also shows positive effects in the tropics, but hardly any in arid regions, these effects are insufficient to fully compensate warming-induced yield reduction even at low levels of warming. Tropical regions are also not very responsive to introducing irrigated production systems so that maintaining current crop productivity under warming is particularly challenging in the tropics. Here we have used the largest available dataset of model simulations at global scale to present the most comprehensive approach for simulating temperature impacts on crop yields. That said, scarcity of global-scale management input data renders simulations at this scale inherently uncertain. Yet, we find good agreement on the globally aggregated impacts and effects of adaptation across the GGCMs, that implicitly represents a broader set of management systems by differing in the parametrization of management-related features. Future research will have to explore the potential for adaptation and intensification in temperate and continental climate zones to contribute to future food security and will have to identify ways how the double burden of strong climate change impacts and low adaptation potential in the tropical and arid climate zones can be alleviated.

2.6 Acknowledgments

Data are made available at a central open-access repository (zenodo.org). DOIs are referenced in Table 2.3. S.M. and C.M. acknowledge financial support from the MACMIT project (01LN1317A) funded through BMBF (Germany). A.C.R. received support from the NASA Earth Sciences Division via the NASA GISS Climate Impacts Group (USA). J.J. received funding from the Open Philanthropy Project with partial support from the U. Chicago

RDCEP center (NSF grant #SES-146364). F.Z. acknowledges financial support from the BioNex Project (031B0230B) funded by BMBF (Germany). W.L. was funded by the Early Postdoctoral Mobility Fellowship of the Swiss National Science Foundation (P2EZP2_175096). T.A.M.P. was supported by the European Commission's 7^{th} Framework Programme, under Grant Agreement number 603542 (LUC4C). This is paper number 40 of the Birmingham Institute of Forest Research.

3

Modelling cropping periods of grain crops at the global scale

Sara Minoli[1,*] Dennis B. Egli[2] Susanne Rolinski[1] Christoph Müller[1]

[1]Potsdam Institute for Climate Impact Research (PIK), Member of the Leibniz Association, Climate Impacts and Vulnerabilities, P.O. Box 60 12 03, D-14412 Potsdam, Germany [2]Department of Plant and Soil Sciences, University of Kentucky, Lexington, KY 40546-0312

[*]Corresponding author

Highlights

- Global crop models require information on cropping periods to represent cultivar diversity.
- Crop maturity (or harvest) dates can be estimated from climate, crop physiological parameters and agronomic principles.
- We propose a method for applications in global modelling studies for dynamically representing adaptation to climate change.

DOI: https://doi.org/10.1016/j.gloplacha.2018.12.013

Abstract

Crop models require information on both weather and agronomic decisions to simulate crop productivity and to design adaptation strategies. Due to the lack of observational data, previous studies used different approaches to determine sowing dates and cultivar parameters. However, the timing of harvest has not yet been sufficiently analyzed. Here we propose an algorithm to determine location-specific maturity (or harvest) dates for applications in global modelling studies. Given a sowing date and the climatic conditions, the algorithm returns a suitable maturity date, based on crop physiological parameters and agronomic principles. We test the method on a global land area with a spatial resolution of 0.5° against global reported datasets for major grain crops: winter-wheat, spring-wheat, rice, maize, sorghum and soybean. A single set of rules is able to largely reproduce the observed harvest dates of the six grain crops globally, with a mean absolute error of 19 (maize) to 45 (rice) days. In temperate regions, the temperature seasonality is the major driver of cropping calendars. In sub-tropical regions, crops are grown to match water availability. In the case of limiting growing seasons, the crop cycle is shortened or extended to avoid stressful periods. In the case of long-lasting favorable conditions the crop cycle is shorter than what the growing season would allow. We find that cropping periods can be largely defined by climate and crop physiological traits. The timing of the reproductive phase is shown to be a general criterion for selecting grain crops cultivars. This work will allow for dynamically representing adaptation to climate change by adjusting cultivars and represents a first step towards improved crop phenology simulations by global-scale crop models.

Keywords: cropping calendar; maturity date; growing period; cultivar; phenology; temperature threshold; agricultural management; modelling.

3.1 Introduction

According to the fifth IPCC Assessment Report (IPCC, 2013) over the $21st$ century global mean temperatures will continue to rise, with stronger trends over land, and future precipitation changes will result in exacerbated patterns of wet and dry regions. Changes in climatic factors affect crop growth and therefore the productivity of agricultural systems, posing challenges to the sustenance of human societies (Asseng et al., 2015). Realistic representation of agricultural systems is a major concern in the context of global change studies (Makowski et al., 2014). Agronomic practices, including crop management, characterize agroecosystems and are crucial in defining adaptation strategies (Ainsworth and Ort, 2010; Tomich et al., 2011; Porter et al., 2014). The choice of crop cultivar is the foremost management option to optimize crop productivity, and to adapt to climate change (e.g. Singh, Prasad, and Reddy (2013), Macholdt and Honermeier (2016), and Challinor et al. (2016)). Crop cultivars are bred for different traits, such as phenology, habit, productivity, vigor, resistance to pathogens, seed quality, etc. Out of these, phenological traits are prioritized in most cases, because of the importance in matching the plant cycle to growing season conditions, such as temperature or water supply (Sedgley, 1991; Craufurd and Wheeler, 2009).
Crop phenological development constitutes a relevant source of crop model uncertainties (Koehler et al., 2013; Jägermeyr and Frieler, 2018). Models typically simulate the crop phenology based on the thermal time concept (Ritchie and Nesmith, 1991; Wang et al., 2017). Starting from the sowing (or planting) date growing-degree-days are accumulated until thermal unit requirements are met, corresponding to crop maturity (or harvest) date (e.g. Kucharik and Brye (2003)). Reduction factors can be included to eventually simulate the sensitivity to photoperiod and vernalization of some crops. Thermal unit requirements are therefore key parameters of the majority of crop models, that are used to represent the cultivar diversity and that are typically the first to be calibrated for matching the crop cycle duration (Archontoulis, Miguez, and Moore, 2014).
Due to a lack of information, different approaches have been developed to represent cultivar diversity distribution in global-scale models. Before the first global datasets on sowing and harvest dates were published (Portmann, Siebert, and Döll, 2010; Sacks et al., 2010; Bondeau et al., 2007) modelled crop-specific sowing dates as a function of climate and the thermal unit requirements as directly dependent on the sowing date, so that e.g. crops sown in warmer climates would require more growing-degree-days to complete their cycle. Similarly, Lindeskog et al. (2013) used a 10-years running mean of thermal unit requirements between default sowing and harvest date limits.
Global datasets can be used to prescribe sowing dates and to directly calibrate crop models in order to match observed harvest dates (Deryng et al., 2011; Drewniak et al., 2013; Elliott et al., 2015). Such approach is possible if observations are available, which limits it applicability to only those areas where the crop is currently grown and observational data sets are of sufficiently good quality. Moreover, if applied under e.g. future climate scenarios, it does not allow for accounting for eventual adjustments in cultivars selection so that assessments of

climate change impacts on agricultural productivity often assume static cultivar selection (Rosenzweig et al., 2014).
To overcome this, van Bussel et al. (2015) derived algorithms to compute location-specific phenological parameters (thermal unit requirements and photoperiod factors) from climatic variables. The algorithm, tested on wheat and maize only, can be applied also outside the current cropland as well as under climate change. One limitation is that it requires a model that uses the specific response functions to temperature and photoperiod applied by the authors. However, crop models can be very diverse in the mathematical functions they use, which themselves constitute a large source of model diversity and of uncertainty (Wang et al., 2017).
Another approach is to estimate sowing and harvest dates, and to use these for model phenology parametrization, similarly to prescribing observed datasets (Mathison et al., 2018). Sacks et al. (2010) found that sowing dates of wheat and maize are dependent on temperature, and can be predicted by fixed temperature thresholds, especially in temperate regions. Waha et al. (2012) simulated sowing dates of several crops at the global scale, taking into account both temperature and precipitation. Other approaches were proposed for regional applications, to estimate sowing dates based on soil temperature and soil moisture (Dobor et al., 2016) or both sowing and harvest dates based on the monsoon onset and retreat (Mathison et al., 2018). In this paper we develop an algorithm to determine location-specific cropping periods for applications in global modelling studies so that adaptation in growing periods under climate change can be explicitly addressed. The approach can be used in combination with either prescribed or computed sowing dates. Given a sowing date, the algorithm returns a suitable maturity (or harvest) date, based on a) crop physiological parameters; b) climatic conditions; c) agronomic principles for maximizing crop productivity. We test the method on a global land area with a spatial resolution of 0.5° against global reported datasets.

3.2 Methods

3.2.1 Overview

The purpose of the model is to estimate location-specific average maturity dates of grain crops. The model has been designed particularly for applications in global scale studies, to allow for calibrating long-term average phenology (e.g. thermal unit requirements) in crop models, in order to represent geographical patterns of crop cultivar diversity and their adaptation.
Only major grain crops were included in this study, in particular winter-wheat (*Triticum sp. L.*), spring-wheat (*Triticum sp. L.*), rice (*Oryza sativa L.*), maize (*Zea mays L.*), sorghum (*Sorghum bicolor L. Moench*), and soybean (*Glycine max L. Merr.*). These crops have dry seeds (grains) as the harvestable product. Moreover, only rainfed cultivation systems were considered.
The model unit consists of two entities: a human-agent (individual farmer) and a grain crop species, and two location-specific exogenous drivers: the climate and the average crop sowing date. Farmers are characterized by their location (grid cell) and their knowledge about

the best growing conditions for each crop. Crops are characterized by a set of parameters, which are the agronomic potential duration of their crop cycle (sowing to maturity) and the repartition of this cycle into a vegetative and a reproductive phase. The latter phase is, in turn, characterized by thresholds of base and optimum temperatures and of two different soil moisture indicators. The model is run on a global-land grid at 0.5° x 0.5° spatial resolution and returns for each grid cell a long-term average daily maturity date (state variable).
In a given year, the farmer grows a given crop in a given location and makes a decision on the best sowing date and on which cultivar to grow. The model we present here focuses on the cultivar choice. Models for computing both average and yearly sowing dates are already available, therefore we use sowing dates as exogenous variables. Each farmer considers the experienced climate and seasonality of the previous 20 years, as well as crop-specific environmental limits to identify the most suitable growing period (sowing-to-maturity time) for the considered grain crop.
The modelling workflow (Figure 3.1a) includes 1) the review of literature on crop physiological parameters, from which we derived crop temperature parameters; 2) the analysis of climate data and of observed crop calendars, from which we estimated the water availability parameters; 3) the development and parametrization of the rules to estimate the maturity date; 4) the evaluation of the rule against observed crop calendars; 5) the re-calibration of the parameters within the predefined range. Figure 3.1b shows the decision tree for the agronomic rules to compute maturity dates (grey box in 3.1a).

3.2.2 Model design concepts

Phenological development largely determines the suitability of a crop for a certain range of environmental conditions (Slafer et al., 2015). We distinguish between *"growing seasons"* and *"growing periods"*. The growing season is the period of time in the year during which environmental conditions are suitable for a given crop to growth, while the crop growing period is the period of time from sowing to maturity (Waha et al., 2013). Therefore, the growing season might be longer than the growing period, as in some cases there is no advantage of growing a crop longer than needed for maximizing yield.
We review agronomical principles for adapting crop phenology to local climate. We formalize these principles by 1) choosing a representation of the phenological cycle common to all grain crops; 2) deriving crop-specific environmental limits from literature; 3) defining a classification of agro-climatic zones; 4) defining rules to identify the most suitable cropping period for the considered grain crops in each location (grid cell). A cropping period is identified as "most suitable" when the reproductive growth phase is maximized while the risk of encountering stressful environmental conditions is minimized.

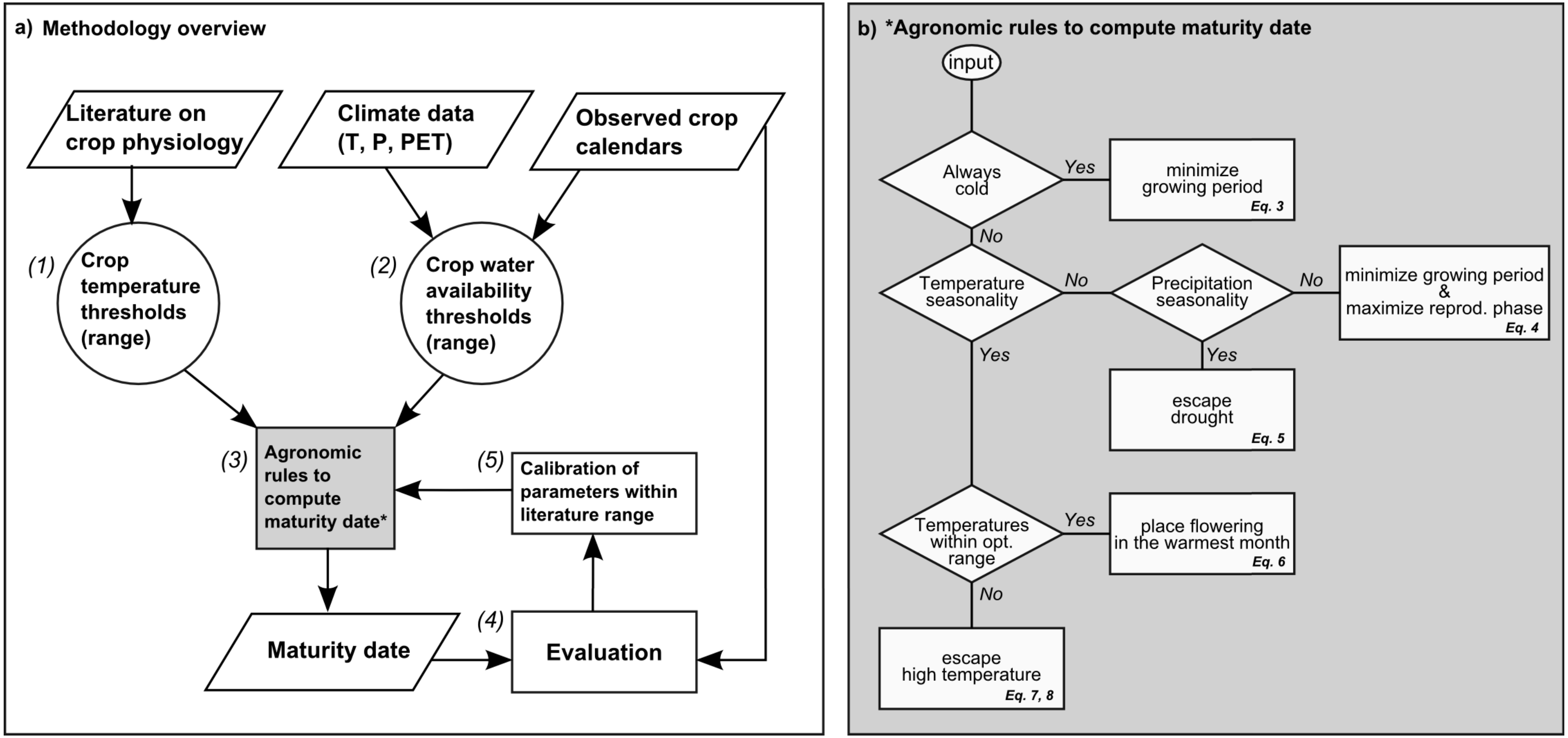


Figure 3.1: Representation of the modelling workflow (a) and details of the agronomic rules to compute the maturity dates (b). In (a) the parallelograms represent inputs or outputs, circles represent parameters, rectangles represent processes. In (b) diamonds are decision and rectangles are the maturity date rules.

3.2.2.1 Agronomic principles for identifying the most suitable cropping period

To be suitable, a grain crop must flower sufficiently early for seeds to mature while favorable conditions persist. However, if flowering is too precocious, plant growth may be insufficient to sustain seed yield (Lawn et al., 1995). The crop biomass production is indeed a cumulative process that requires time to first capture solar radiation to convert its energy into photosynthetic assimilates, and then to build the reproductive and the storage organs from these. The total biomass can be maximized by letting the crop use as much solar radiation as possible, by matching the length of the phenological development to the length of the growing season (Egli, 2011). In the case of short growing seasons, this way also highest grain yields are gained as often occurs at high latitudes (Peltonen-Sainio et al., 2015) or altitudes, or in very dry environments (Bodner, Nakhforoosh, and Kaul, 2015). On the contrary, in the case of long and favorable seasons, a crop cycle shorter than the growing season may be sufficient to obtain the maximum grain yield. In particular, this is valid when the total growth length exceeds the duration where reproductive growth, and therefore yield, stops increasing (Egli, 2011). However, long growing seasons might also include or terminate with stressful periods. Under these conditions, the use of late- or early-maturing cultivars may be strategic for shifting the reproductive growth to a more favorable period, to avoid stresses and yield losses (Craufurd and Qi, 2001; Clerget et al., 2008; Egli, 2011).
For an effective crop establishment, sowing should be carried out when soil temperature allows for rapid seed germination and seedlings emergence (Waha et al., 2012). Grain yield can be maximized when the crop is exposed to an optimum range of air temperature, and it progressively declines as temperature increases above this range (Hatfield et al., 2011a). Grain crops are generally more sensitive to high temperatures during the reproductive than the vegetative development stages (Farooq et al., 2011; Singh, Prasad, and Reddy, 2013).
To enable yield formation, soil water content must be sufficient to sustain crop growth throughout the entire growing period. Ensuring an adequate water supply during grain filling is particularly critical for grain yield in annual crops (Asseng et al., 2015). Therefore, in regions strongly characterized by precipitation seasonality, the growing season is dependent on the onset and cessation of the rain (Araya, Keesstra, and Stroosnijder, 2010; Bodner, Nakhforoosh, and Kaul, 2015; Mathison et al., 2018).

3.2.2.2 Definition of the crop phenological cycle and environmental limits

The duration of the total growing period (GP) can vary widely among locations, crops and cultivars. We set lower (GP_{min}) and upper (GP_{max}) limits as indications of the biological (or agronomical) potential of the crops. We consider the *vegetative phase* (GPV) to have a flexible duration, while we assume the *reproductive phase* (GPR) to have a constant length equivalent to its maximum if the growing period is long enough to support this (Table 3.1). The time allocated to vegetative and reproductive growth follows a similar pattern in all grain crops. According to Egli (2011), the actual yield formation period (reproductive phase) becomes nearly constant after approaching a maximum (horizontal asymptote). Conversely, the vegetative phase increases steadily with the total growth length. All crop species share the same relationship, except maize, which allocates a longer time to the reproductive phase. We call GP_{maxrp} the minimum growing period for attaining the longest reproductive

Table 3.1: Crop-specific parameters (growth phase lengths) of the maturity date function. Phases are defined by the BBCH scale (Meier, 1997). The total growing period (GP) is defined as the sum of vegetative (GPV) and reproductive (GPR) growing periods. GPmin and GPmax are the minimum and the maximum allowed GP, respectively. GPmaxrp is the minimum growing period for attaining the longest reproductive phase. The parameter GPR denotes the maximum length of the reproductive growing period for growing periods longer than GPmaxrp.

growth phase	vegetative	reproductive		limits of GP		maturity to harvest
BBCH	(00-69)	(70-89)		(00-89)		(89-99)
parameter	GPV	GPR	GPmin	GPmax	GPmaxrp	MatHar
unit	(days)	(days)	(days)	(days)	(days)	(days)
winter-wheat	internal[1]	40[2]	60[2]	330[3]	120[2]	7[4]
spring-wheat	internal[1]	40[2]	60[2]	180[2]	120[2]	7[4]
rice	internal[1]	40[2]	60[2]	180[2]	120[2]	7[4]
maize	internal[1]	60[2]	60[2]	180[2]	120[2]	21[4]
sorghum	internal[1]	40[2]	60[2]	180[2]	120[2]	0[4]
soybean	internal[1]	40[2]	60[2]	180[2]	120[2]	21[4]

(1) internally computed in the model
(2) Egli (2011)
(3) Rukhovich et al. (2007)
(4) Elliott et al. (2015)

phase. For all growing periods that are shorter than GP_{maxrp}, the GPR is shorter than the parameter specified in 3.1. However, as the model does not simulate anthesis dates, the length of the actual GPR is not explicitly computed.

In this work we represent the crop cycle by just two main phases, namely the vegetative and the reproductive phase. There are a number of metrics to describe the phenological development of the grain crops (e.g. BBCH (Meier, 1997), Vn-Rn stages, etc.). In several crops, these two periods overlap, so that they can be arbitrarily defined depending on the scope of the work. Here we call *vegetative* (GPV) the phase from sowing, or more precisely from germination (BBCH 09), to the end of flowering (BBCH 69), while we call *reproductive* (GPR) the phase lasting from the beginning of the grain development (BBCH 70) to the grain physiological maturity (BBCH 89). Additionally, we take into account the senescence phase (MatHar) from physiological maturity to the stage of harvestable grain (BBCH 99) (Table 3.1).
We use cardinal *base temperatures for reproductive development* (T_{baseRD}) and *optimum temperatures for reproductive production* (T_{optRP}) (Hatfield et al., 2011a), as thresholds to identify the best time for the crop reproductive phase, and consequently for the end of the growing period of a crop in a given location (Table 3.2). Together with temperature, the crop cycle is largely influenced by water availability. We use water availability thresholds of $PPET_{ratio}$ and $PPET_{ratioDIFF}$ (Table 3.2) to identify the last convenient period for crop growth.

Table 3.2: Crop-specific parameters (temperature (°C) and water thresholds (dimensionless)) used in the maturity date function and their reference values from literature. TbaseRD is the base temperature for reproductive development, ToptRP is the optimum temperature for reproductive production (grain-filling), PPETratio is the ratio between precipitation and evapotranspiration in a month, PPETratioDIFF is the monthly trend in moisture conditions. Mean and ranges of parameter values found in literature are from five review studies (Porter and Gawith, 1999b; Hatfield et al., 2011a; Farooq et al., 2011; Singh, Prasad, and Reddy, 2013; Sánchez, Rasmussen, and Porter, 2014). Temperature thresholds for sowing can be found in (Waha et al., 2012).

Parameter	T_{baseRD}				T_{optRP}				$PPET_{ratio}$	$PPET_{ratioDIFF}$
Unit	(°C)				(°C)				(-)	(-)
	values found in literature			values used in this study[1]	values found in literature			values used in this study[2]	values used in this study[3]	values used in this study[3]
Crop	mean	range	ref.		mean	range	ref.			
winter-wheat	9.5	(9-12)	a	1	20.7	(15-25)	a	21 (12-25)	NA	NA
	1		b		15	(15-25)	b			
					21.3	(12-22)	c			
spring-wheat	9.5	(9-12)	a	1	20.7	(15-25)	a	25 (12-25)	0.5 (0-1)	0.5 (0.1-0.5)
	1		b		15	(15-25)	b			
					21.3	(12-22)	c			
rice	8		b	8	25	(23-26)	b	24 (20-31)	1.0 (0-1)	0.5 (0.1-0.5)
	20.7	(12-14)	d		24.2	(20-31)	d			
maize	8		b	7	24	(18-30)	b	30 (18-30)	0.5 (0-1)	0.5 (0.1-0.5)
	8	(7-16)	d		< 30		e			
					26.4	(25-30)	d			
sorghum	8		b	8	25	(25-28)	b	25 (25-28)	0.5 (0-1)	0.5 (0.1-0.5)
soybean	6		b	6	23	(22-24)	b	23 (22-27)	0.5 (0-1)	0.5 (0.1-0.5)
					23	(23-27)	e			

(1) values of TbaseRD used in this study were selected as the minimum of the overall range reported in the references.
(2) values of ToptRP used in this study based on the sensitivity analysis. In brackets the overall range reported in the references.
The selected value was chosen as the one that can best reproduce the observed cropping calendars (minimum MAE).
(3) values of PPETratio and PPETratioDIFF used in this study based on the sensitivity analysis. In brackets the tested range.
The selected value was chosen as the one that can best reproduce the observed cropping calendars (minimum MAE).
(a) Porter and Gawith (1999b)
(b) Hatfield et al. (2011a)
(c) Farooq et al. (2011)
(d) Sánchez, Rasmussen, and Porter (2014)
(e) Singh, Prasad, and Reddy (2013)

3.2.2.3 Rule-based decision making

We assume one farmer agent for each grid cell, and that all farmers have the same knowledge and crop cultivar availability. The decision making on the most suitable average maturity date for a certain crop and location is modelled by a set of rules (see below for the details). In a given year, the farmer takes into account the long-term average temperature and precipitation seasonality of the previous 20 years in that location and the environmental limits to the crop reproductive growth to define the growing period that maximizes the reproductive growth duration, while minimizing the risk of encountering stressful environmental conditions. We assume that the farmer does not rely on any information about pre-season weather forecasts, but that he/she expects the weather of the year-of-simulation to be close to the previous 20 years average.

3.2.3 Model details

3.2.3.1 Climate data and statistics

In this model application, we simulate maturity dates for the year 2000. As we assume farmers to make decisions on the preceding 20 years, we computed monthly statistics for the period 1980-1999. Data of the following climatic variables were derived from the AgMERRA global climate forcing dataset with daily time steps (Ruane, Goldberg, and Chryssanthacopoulos, 2015), that we use at 0.5° x 0.5° spatial resolution (Elliott et al., 2015). We computed the monthly mean temperature (T, °C) as the average of the daily mean temperature of all days of each month: the monthly cumulated precipitation (P, mm month^{-1}) as the sum of the daily precipitation in that month; the monthly cumulated potential evapotranspiration (PET, mm month^{-1}) as the sum of the daily PET rate in that month, estimated with the Priestley-Taylor equation (Priestley and Taylor, 1972), with a Priestley-Taylor coefficient of 1.391 (Gerten et al., 2004). Additionally we computed two monthly dryness indices based on P and PET. The simple P to PET ratio (PPET$_{ratio}$, dimensionless, Eq. 1) indicates the water surplus or deficit with respect to the plants water demand (Thornthwaite, 1948; Sacks et al., 2010; van Wart et al., 2013), and the PPET$_{ratio}$ difference of two consecutive months (PPET$_{ratioDIFF}$, dimensionless, Eq. 2) indicates the monthly trend in moisture conditions. If PPET$_{ratioDIFFm}$>0, the trend is declining, indicating that the following month (m+1) is dryer than month m.

$$PPET_{ratio_m} = P_m / PET_m \tag{3.1}$$

$$PPET_{ratioDIFF_m} = PPET_{ratio_m} - PPET_{ratio_{m+1}} \tag{3.2}$$

Long-term daily averages are obtained by linear interpolation of the monthly statistics, to cope with fluctuations of daily values, and to allow for the consideration of monthly input data.

3.2.3.2 Agro-climatic zones classification

Agro-climatic zones can be defined based on homogeneity in the weather variables that have greatest influence on crop growth and yield (van Wart et al., 2013), such as temperature and water availability. According to Waha et al. (2012) we define three climate zones (seasonality types) by the intra-annual variability (coefficient of variation, CV) of T (CV_{temp}) and P (CV_{prec}). These are computed on monthly climate data:

1. no temperature and no precipitation seasonality (NO SEAS.: CV_{prec} ≤0.4 AND CV_{temp} ≤0.01);
2. precipitation seasonality (PREC. SEAS.: CV_{prec} >0.4 AND CV_{temp} ≤0.01);
3. mixed seasonality (MIXED SEAS.: CV_{temp} >0.01 AND (CV_{prec} ≤0.4 OR CV_{prec} >0.4)).

In addition to that, we consider the temperature of the warmest month (max(T)) and compare it to the crop-specific thresholds for reproductive growth (T_{baseRD}, T_{optRP}). Within each seasonality type, three possible temperature configurations can occur:

(a) temperatures never reach the base temperature (max(T)<T_{baseRD}), so that the crop cannot complete its reproductive cycle, and therefore cannot productively be grown;
(b) temperatures exceed T_{baseRD}, while never exceeding the optimum temperature T_{optRP}, so that at least part of the year is available for the crop to go through its reproductive cycle;
(c) temperatures exceed T_{optRP}, so that at least part of the year is characterized by supra-optimal temperatures for yield production (see Appendix B[1], Section A).

3.2.3.3 Function to compute the maturity date

The set of rules for estimating the end of the growing period (date of physiological maturity) is graphically described in Figure 3.1b and in Appendix B (Section A) and all parameters are listed in 3.1 and 3.2. The seasonality type determines which climatic factor (temperature or precipitation, or their combination), is the most limiting for the total crop cycle. Differences between the monthly mean temperature (T) level and T_{baseRD} and T_{optRP} define the existence of a suitable period for the reproductive growth. In the following formulas, rule numbers 1, 2, 3 refer to the seasonality types NO SEAS., PREC. SEAS, MIXED SEAS., and letters a, b, c, refer to the temperature levels LOW T., MID T., HIGH T. respectively. Moreover, Sowing day is the day of the year on which the growing period starts and it can be either prescribed or simulated by any algorithm (e.g. Waha et al. (2012)), Tmax day is the day on which the warmest temperature is reached (here assumed to be the midday of the warmest month); T_{opt} day_1 is the first day on which T > T_{optRP}, T_{opt} day_2 is the last day of T > T_{optRP}. $PPET_{ratio}$ day is the first day on which the $PPET_{ratio}$ or PPETratioDIFF falls below the defined threshold (Table 3.2). The rule for simulating the maturity date is defined as follows (see also Appendix B, Section A):
In regions characterized by very low temperatures, always below the base temperature for reproductive development (max(T) < T_{baseRD}), the shortest maturing cultivar is chosen,

[1]Supplementary Information for this chapter are reported in Appendix B of the thesis. The appendix is divided in sections identified by the letters A-G, as from the original publication.

regardless of the seasonality type. The growing period is set to GP_{min} (agro-climatic zones 1.a, 2.a, 3.a; Eq. 3). This is a rule to ensure functionality at the global scale, and to allow the simulation in those environments where crops in fact cannot be grown.

$$Maturity\ day = Sowing\ day + GP_{min} \tag{3.3}$$

In warmer regions (max(T) $>$ T_{baseRD}) without temperature seasonality, the crop can complete the reproductive cycle. We do not account for possible limitations due to too high temperature (failure temperature). If there is also no precipitation seasonality (NO SEAS. in Appendix B, Section A), the growing period is set equal to GP_{maxrp} (agro-climatic zones 1.b, 1.c; Eq. 4).

$$Maturity\ day = Sowing\ day + GP_{maxrp} \tag{3.4}$$

Otherwise, under precipitation seasonality (PREC. SEAS. in Appendix B, Section A), the maturity date might be anticipated to escape drought. The reproductive phase (GPR) is set to start towards the end of the wet-season ($PPET_{ratio}$ day), to guarantee soil water availability until maturity (agro-climatic zones 2.b, 2.c; Eq. 5).

$$Maturity\ day = min \begin{cases} PPET_{ratio} day + GPR \\ Sowing\ day + GP_{maxrp} \end{cases} \tag{3.5}$$

In regions with temperature and eventually precipitation seasonality (MIXED SEAS. in Appendix B, Section A), the maturity date is determined by setting the reproductive phase in the most suitable period of the year, to minimize stresses, and to leave sufficient time to develop photosynthetic organs. The most limiting factor is the one that occurs first. The growing period cannot be shorter or longer than GP_{min} or GP_{max} respectively. Under mid temperature conditions (T_{optRP} $>$ max(T) $>$ T_{baseRD}), the reproductive phase starts at the warmest day of the year (Tmax day) (agro-climatic zone 3.b; Eq. 6).

$$Maturity\ day = min \begin{cases} max(Sowing\ day + GP_{min}; T_{max} day + GPR) \\ max(Sowing\ day + GP_{min}; PPET_{ratio} day + GPR) \\ Sowing\ day + GP_{max} \end{cases} \tag{3.6}$$

Under high temperature conditions (max(T) $>$ T_{optRP}) (agro-climatic zone 3.c) we distinguish between winter and spring crop types: Winter crops have a long time available for their vegetative growth that they can exploit during both autumn and spring. Maturity occurs as soon as the temperature exceeds the optimum temperature (T_{opt} day_1), so that the crop can escape high temperature stress by maturing beforehand. We assume no water limitations (Eq. 7).

$$Maturity\ day = min \begin{cases} max(Sowing\ day + GP_{min}; T_{opt} day_1) \\ Sowing\ day + GP_{max} \end{cases} \tag{3.7}$$

Spring crops need to use the first part of the season for developing photosynthetic organs, so that the earliest period of the season with optimal conditions for reproductive growth is in fact used for the vegetative phase. The start of the reproductive cycle is set when the mean temperature falls below the optimum temperature (T_{opt} day$_2$), to avoid the risks of high-temperature stress in the middle of the growing period, and to ensure the best conditions for the reproductive phase (Eq. 8).

$$Maturity\ day = min \begin{cases} max(Sowing\ day + GP_{min}; T_{opt}day_2) \\ max(Sowing\ day + GP_{min}; PPET_{ratio}day + GPR) \\ Sowing\ day + GP_{max} \end{cases} \tag{3.8}$$

For comparison with observational datasets, which report harvest dates rather than maturity dates, we estimate harvest dates by adding a crop-specific maturity to harvest (MatHar) time (Table 3.1) to the computed maturity dates (Eq. 9).

$$Harvest\ day = Maturity\ day + MatHar \tag{3.9}$$

In summary, the end of the cropping period can be triggered by one of the following reasons: the choice of the earliest-maturing cultivar (GP_{min}); the cultivar with the longest grain-filling phase (GP_{maxrp}); the latest-maturing cultivar (GP_{max}); or the occurrence of water limitations (w. lim.); mid-temperature limitations (mid. t.); high-temperature limitations (high t.).

3.2.3.4 Model setup

We used R (R Core Team, 2015) for the model implementation, the data preparation, and the overall analysis. In order to examine its performance and sensitivity, we run the model with different parametrization settings and input data (Table 3.3).

Table 3.3: Summary table of model runs.

Run setup ID	Nr. of runs per crop	Parametrization	Sowing date
1	315	sensitivity	MIRCA2000
2	1	calibrated	MIRCA2000
3	1	calibrated	SAGE
4	1	calibrated	Simulated (Waha et al., 2012)

3.2.3.5 Parametrization

For simplicity, we assume unique values of the model parameters to be valid globally. We derived parameters related to the growth phase lengths (GPR, GP_{min}, GP_{maxrp}, GP_{max}, MatHar) (Table 3.1) and to temperature thresholds (T_{baseRD}, T_{optRP}) from literature (Table 2). We were not able to find reference values of $PPET_{ratio}$ and PPETratioDIFF thresholds or any other moisture-related thresholds for any specific growth phase. We therefore explored the patterns of the two variables throughout the observed growing periods (MIRCA2000). We find that except for winter- and spring-wheat, for all other crops $PPET_{ratio}$ starts declining from about two months before harvest, with the stronger negative trend ($PPET_{ratioDIFF}$) about one month before harvest (Appendix B, Section C).

3.2.3.6 Sensitivity analysis and calibration

We perform a sensitivity analysis of the maturity date function to T_{optRP}, $PPET_{ratio}$ and PPETratioDIFF thresholds. For this we used MIRCA2000 sowing dates as the model input data. As the representativeness of the reported T_{optRP} range is not clear for each grain crop considered here, we also test whether the model behavior is substantially different outside the reported temperature range. Therefore, we run the model with different temperature thresholds ranging from 2°C below the lowest reported temperature threshold to 2°C above the reported temperature threshold in increments of one degree. For the moisture related thresholds we used ranges of representative values (0, 0.5, 1 for $PPET_{ratio}$ and 0.1, 0.2, 0.3, 0.4, 0.5 for $PPET_{ratioDIFF}$). Subsequently, we calibrate the function to MIRCA2000 by testing which thresholds can best reproduce the reported cropping calendars. We select the parameter set for each crop that leads to the lowest global area-weighted Mean Absolute Error (MAE) (see Section 3.2.4).

3.2.3.7 Model response to input data

We also compute cropping calendars by combining the calibrated maturity date function presented above with three different sowing date inputs: MIRCA2000, SAGE and simulated with sowing date function proposed by Waha et al. (2012).

3.2.4 Model evaluation

To evaluate the model's skill in estimating maturity dates, we compare global-scale simulations for the six crops for the year 2000 to the two most applied global cropping calendar datasets (MIRCA2000, Portmann, Siebert, and Döll (2010), and SAGE, Sacks et al. (2010) in the modelling community. In order to exclude the uncertainty due to the sowing date, we prescribe the sowing date from the observation-based dataset. The MIRCA2000 (v1.1) dataset (Portmann, Siebert, and Döll, 2010) provides monthly cropping periods of 26 crop types, as well as the associated growing areas, available at 0.5° grid cell resolution, representative for the time period 1998 to 2002. For our analysis, we refer to the rainfed sub-crops with the largest reported area for rice, maize, sorghum, soybeans. For wheat, we merged sub-crops 1 and 2 and distinguished between winter- and spring-wheat as follows (map shown in Appendix B, Section B). We assume that the growing season refers to winter-crop if (i) the cropping period includes the coldest month of the year, and (ii) the mean temperature of the coldest month is lower than 10°C. The SAGE dataset (Sacks et al., 2010) provides typical planting and harvesting dates for 19 crops, available at 0.5° resolution, representative for the time for the 1990s or early 2000s. In comparison with MIRCA2000 this dataset (i) has a daily resolution; (ii) distinguishes between winter- and spring-wheat; (iii) does not distinguish irrigated and rainfed crops; (iv) does not include data on crop area; (v) is often uniform in large administrative units such as countries. For the evaluation of the goodness-of-fit of the model to the observed datasets, we employ the Mean Absolute

Error (MAE) index (Jachner, Boogaart, and Petzoldt, 2007), area-weighted as in Waha et al. (2012).

$$MAE = \frac{\sum_{i=1}^{n} |S_i - O_i| \cdot A_i}{\sum_{i=1}^{n} A_i} \tag{3.10}$$

Where n is the number of observations (grid-cells with a reported harvest date), i is the index of the grid cell, S and O are respectively the simulated and observed date (months) of grid-cell i, A is the cropped area (ha) of grid-cell i. For weights, we use the crop area of MIRCA2000, which we also employ for masking uncropped areas in maps when displaying results.

3.3 Results

3.3.1 Model sensitivity and parametrization

The results of the model calibration reveal (Appendix B, Section D) that, with the exception of sorghum, temperature thresholds outside the reported ranges (Table 3.2) would not lead to better model performances. For sorghum, the minimum MAE is obtained with a T_{optRP} value of 1°C lower than the reported temperature range, but it is only marginally better than the lowest reported threshold temperature. Rice, soybean and winter-wheat show a U-shaped curve, with a minimum MAE in the middle of the tested temperature range, whereas maize and spring-wheat show best performances at the upper limit of the reported temperature range, but with stable MAE values above this. The sensitivity to $PPET_{ratio}$ and $PPET_{ratioDIFF}$ indicate that most crops, except rice, perform best (minimum MAE) when both parameters are set to 0.5. This indicates that last phases of the crop growth cycles are shorter if there is either a period characterized by low P and/or high PET, or by a drastic change in the precipitation regime from wet to dry. The performance of the model for winter-wheat is completely insensitive to $PPET_{ratio}$ and $PPET_{ratioDIFF}$, as we assume no water limitation in the maturity date rule of this crop (Table 3.2).

3.3.2 Computed maturity dates

3.3.2.1 Aggregated model performances

At the global aggregation level, the calibrated model can largely reproduce the observed harvest months from both MIRCA2000 (calibration dataset) and SAGE (independent dataset), with an absolute error lower than 30 days for all crops except for rice (Fig. 3.2). Specifically, for winter-wheat, spring-wheat, rice, maize, sorghum, and soybean, 82, 78, 61, 93, 82, 91% of the total area respectively, show an error within +/-1 month. The comparison against SAGE results in similar MAE values (Appendix B, Section E) and 90, 77, 54, 79, 58, 92% with an error within +/-1 month. The different criteria for determining the end of the cropping period are distributed across different error classes, so that no systematic error can be detected in any of the rules (Fig. 3.2). High temperature limitations typically do not constrain growing periods of spring-wheat and maize. All crops are mostly grown for periods longer than their lower potential limit (GP$_{min}$), and shorter than their upper-potential (GP$_{max}$).

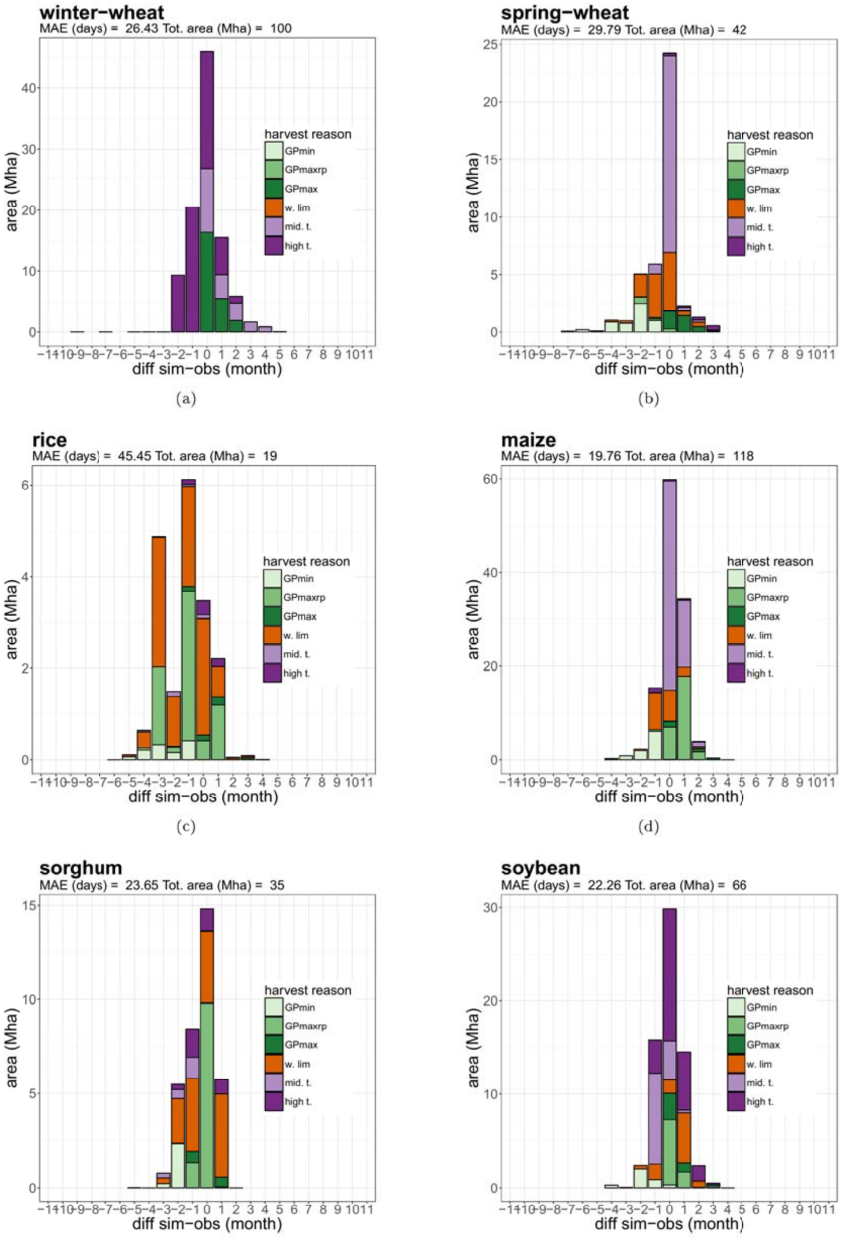


Figure 3.2: Aggregated performances of the model to compute the maturity dates. The bar plot shows the frequency distribution of the difference between simulated and observed (MIRCA2000) harvest dates. The frequency is measured in terms of harvested area (Mha), the sum of all bars is the total area (Mha) of the crop reported by MIRCA2000. The colors indicate the different realized harvest reasons: the choice of the earliest-maturing cultivar (GP_{min}); the cultivar with the longest grain-filling phase (GP_{maxrp}); the latest-maturing cultivar (GP_{max}); or the occurrence of water limitations (*w. lim.*); mid-temperature limitations (*mid. t.*); high-temperature limitations (*high t.*). MAE is the area weighted mean absolute error (days, Eq. 10) for the crop.

3.3.2.2 Global patterns

In this and the following sections of the main text we show results for maize only (Fig. 3.3), as this crop has the largest cultivated area (Fig. 3.2) and diversity of climates (Fig. 3.3(a)).

Results of all simulated crops are presented in Appendix B (Section F), but also discussed in the main text. We concentrate in the main text on the results of the simulation with prescribed sowing dates from MIRCA2000 (Fig. 3.3) and provide a comparison of results with computed sowing dates (Waha et al., 2012) in Appendix B (Section G).

Maize is cultivated in nearly all considered climatic zones (Fig. 3.3(a)) and therefore rules (Appendix B, Section A) for computing the maturity date are very diverse. Maize growing seasons encounter mean temperatures above the optimum (29°C) in sub-Saharan Africa and in India. The remaining maize cultivated area is characterized by average monthly temperature between T_{baseRD} and T_{optRP} for at least part of the year (Appendix B, Sections E and F).

Various factors cause the end of maize growing period across regions (Fig. 3.3(b)). In temperate regions the maize cycle follows the seasonal evolution of temperature (purple color, Fig. 3.3(b)), resulting in fairly long (up to 7 months) total GPs (Fig. 3.3(d)). In some areas, such as around the Mediterranean Sea, sub-Saharan and East Africa, South-East Asia (orange color, Fig. 3.3(b)), the maturity date is triggered by the occurrence of a dry period (3 to 4 months GP). In parts of India and Mexico, either temperature or water limitation occur soon after sowing, determining a very short total GP (2 months). Within the tropics large areas show no constraints for maize to grow for up to 5 months. Spatial patterns of maize harvest date are rather well reproduced by the model (Fig. 3.3(c, e, f)). According to both observations and simulations, large regions of North America, Eastern Europe, and Russia show similar values (no differences in Fig. 2(f)), indicating convergence of maize harvest dates in mid-temperature areas. In these areas the gradients in GPs are therefore a result of gradients sowing dates. Similarly, good agreement with the observation is found in South America, with homogeneous harvest time and GP found over large parts of the continent.

The model systematically overestimates the end of the growing period in Central Africa and Eastern China. Differences between the computed and observed harvest date are found e.g. in Mexico, around the Mediterranean Sea, and in South-Eastern China. In these areas, MIRCA2000 reports homogeneous values, while the model simulates gradients. From Fig. 3.3(f) it can be seen that there is a shift from -1 to +1 months difference across these gradients. For example, harvest in Spain goes from August-September to October progressing from south to north. In these areas, the observations report harvest homogeneously for September.

Compared to maize, the other five crops have growing seasons more likely affected by non-optimal temperatures. In particular, the high temperature rules (1.c, 2.c, 3.c) apply to the largest fraction of the current cultivated area of rice, sorghum and soybean (Figure E1, E3 in Appendix B, Section E), which require cultivars with a longer growing period to avoid the high-temperature during the reproductive phase.

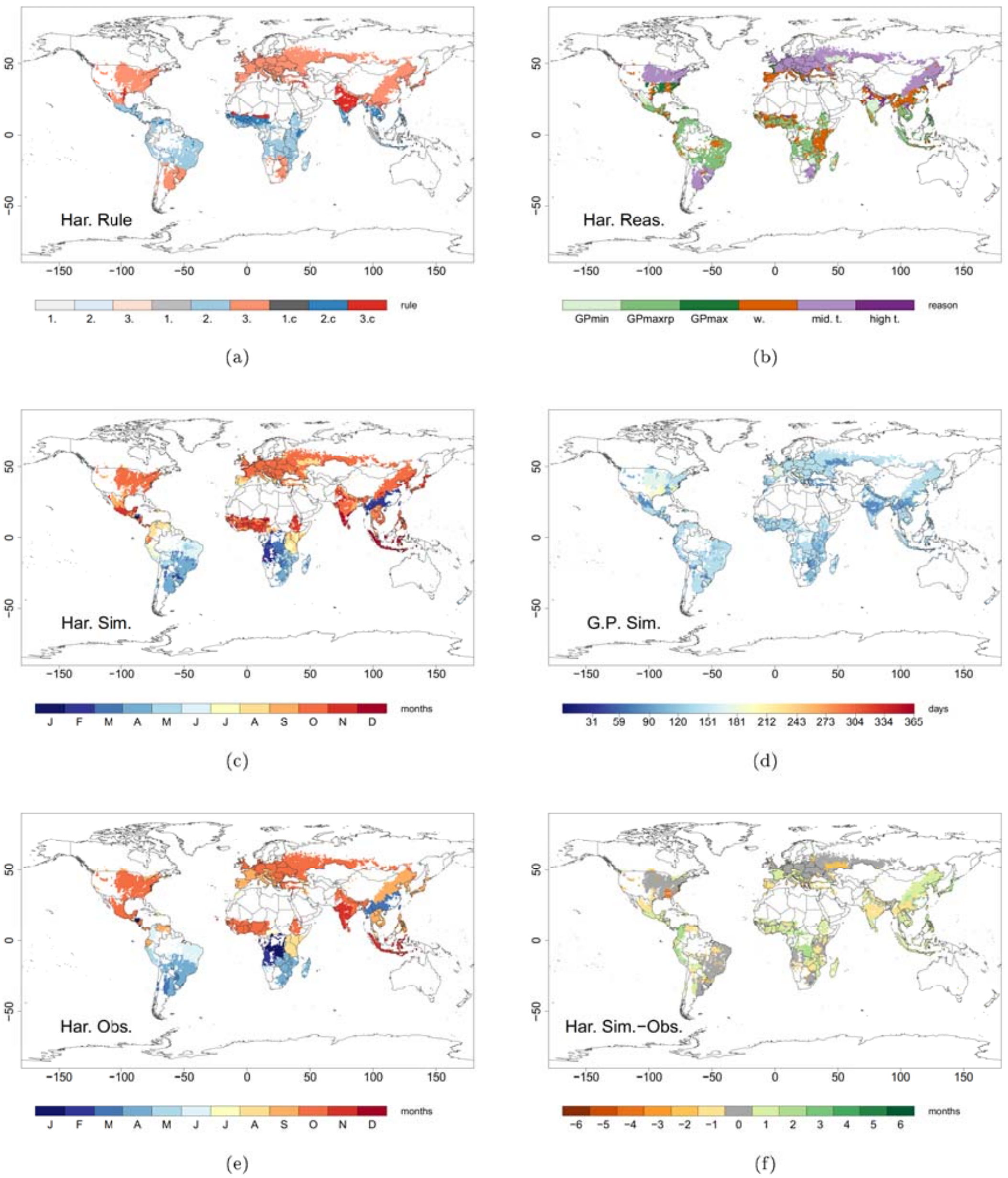


Figure 3.3: Results of the modelling workflow phases and evaluation for maize: (a) agro-climatic zones of cultivation and corresponding rule applied for computing the harvest date (1.a-3.c); (b) realized harvest reason, representing the factor causing the end of the growing period (GP_{min} is earliest-maturing cultivar; GP_{maxrp} is longest grain-fill cultivar; GP_{max} is latest-maturing cultivar; *w.lim* is water limitations; *mid t.* is mid-temperature limitations; *hight t.* is high-temperature limitations.); (c); computed harvest month with our modelling approach, where we have prescribed the sowing date from MIRCA2000; (d) length of the computed total growing period (GP, sowing-to-harvest time); (e) observed harvest month from MIRCA2000; (f) difference between computed and observed harvest month. White color indicates pixels with less than 0.001% maize cultivated area according to MIRCA2000.

Patterns of soybean GP are relatively similar to those of maize, while generally spring-wheat and sorghum show shorter GPs. For winter-wheat GPs are mostly calculated as very long (7 to 11 month), with increasing lengths in colder regions (central-Europe and Russia).

Sub-Tropical regions show quite uniform GP durations and similar among different crops (e.g. maize, sorghum, rice in Sub-Saharan Africa). Though in India, GP differs between crops because the maturity date is triggered by different reasons. Similarly to maize the spatial patterns of harvest dates are well reproduced by the model for all crops. Winter-wheat and soybean show gradients of harvest dates, due to gradients in the driving climatic factors (e.g. temperature patterns in the United States), leading to differences to the observations, which report uniform values within geographical units.

3.3.3 Full simulation of the cropping periods

Results for both simulated sowing and harvest and their difference to MIRCA2000 are shown in Appendix B (Section G). Simulated cropping periods are displayed for the entire global land, therefore also in regions where crops are not currently grown. Simulations and observations show similar degrees of agreement for both sowing and harvest dates, with coinciding spots of largest differences e.g. south-eastern China, southern Brazil, Tanzania for maize (Appendix B, Section G). The duration of the total GP shows good agreement with the observed one, even in the areas where sowing and/or harvest dates deviate from observations. Indeed, the sign of the simulated to observed difference is in most cases the same although there are some exceptions. Winter-wheat in the USA shows at the same time delayed sowing and anticipated harvest, resulting in an overall shorter GP with respect to MIRCA2000. Soybean in south-eastern China results in longer GP, due to an earlier sowing and a delayed harvest.

3.4 Discussion

We show that average maturity (and harvest) dates can be estimated from crop-specific plant physiological parameters and climatic conditions for the majority of currently cropped areas. For the largest part of the global cultivated land the model results are in agreement with both MIRCA2000 (dataset used for model calibration) and SAGE (independent dataset). The mean absolute error (MAE) is close to or lower than about 1 month for all the considered crops. On a local scale or within a single year, a difference of a month in the maturity date of a crop could make a substantial difference e.g. for the crop productivity. However, such an error value is not large when considering the global scale of this study. Similar errors were obtained for sowing dates (Waha et al., 2012) and growing periods (van Bussel et al., 2015; Mathison et al., 2018). Differences can be explained partly by limitations in the modelling approach, and partly by shortcomings in the datasets used for comparison. MIRCA2000 reports dates with a monthly resolution. This means that when using this observation-based dataset as input to models with a daily time step assumptions must be made for converting months to days. This necessarily introduces an uncertainty of about a month in the observations themselves. On the other hand, SAGE has a daily resolution. Despites, its use is also subject to uncertainty due to low resolved spatial patterns (e.g. uniform country values) and to the large reported ranges around sowing and harvest dates. These shortcomings do not leave much room for improving the accuracy in our model evaluation. In addition, the authors of the MIRCA2000 dataset recommend caution in using such cropping dates “in areas where local biophysical constraints differ considerably from average constrains within the calendar unit” (Portmann, Siebert, and Döll, 2010). We find that where the data are homogeneous over large areas, the model can simulate spatial gradients distributed around the average maturity date. In such cases, the simulated maturity dates seem to be more realistic than the observed ones.

The two previously proposed approaches for the estimation of crop maturity or harvest dates that we could find in the literature are more empirically based, as they directly derive rules by crop calendar observations and climate data. The method from van Bussel et al. (2015), computes location-specific cultivar parameters (thermal units requirements, vernalization and photoperiod) with linear-regression models, and from these derives harvest dates. Mathison et al. (2018) models the rice–wheat rotation calendar in South Asia based on the Asian Summer Monsoon. They derive the sowing and harvest date rules by simply computing the difference between onset/cessation of the monsoon and the observed sowing/harvest dates, and determining the weighted area averages from these to derive the rule. With a similar performance in terms of estimation error, our approach has the advantage of being more process-based which allows for better understanding of underlying mechanisms of cropping periods selection and for more explicit assumptions on future crop varieties’ choice scenarios (e.g. different crop sensitivities to temperature, or crop phenological phase durations).

The results show that a single set of rules (with crop-specific parameters) is valid for simulating the average current growing periods of any of the grain crops. Even though the model represents a very complex decision making process in a simplified way, its ability to reproduce global cropping calendar variability and patterns suggests that a few climatic variables and crop physiological limits can explain a large portion of the recent cropping period patterns. This endorses the idea that agricultural practices have been adapting to the climatic conditions experienced by farmers (Olesen et al., 2012). Specifically, it shows that farmers tend to grow the crops under the best available conditions for maximizing crop productivity. In particular, the timing of the reproductive phase seems to be a general criterion for selecting grain crops cultivars. In environments characterized by temperature seasonality, where the first phases of the crop cycles are subject to cooler temperatures (e.g. winter-wheat), it seems a common practice to extend the growing period, and therefore prolong the vegetative development (Appendix B, Section F, panels d), to let the reproductive phase occurring within the warmest season. However, stressful temperatures or water-scarce seasons can require the use of shorter or longer maturing cultivars. In line with previous findings (Egli, 2011; Hay, Porter, et al., 2006; Parent et al., 2018), we assume a much larger flexibility of the vegetative phase length, as compared to a more stable reproductive phase. However, it has been shown that crop breeding has in some cases targeted earlier flowering and extended the reproductive phases (Glotter and Elliott, 2016). As we explicitly parametrize this in our model, it is possible to account for such genetic improvement in future studies.

On farms, when selecting for cultivars and cropping periods, farmers may take into account several factors (e.g. soil conditions, yield potentials, pests and diseases, consumer preferences) that are not explicitly considered in our model. In consequence, as for the simulation of sowing dates (Waha et al., 2012), the model performs very well in regions with clearly climate-defined growing periods, as temperate zones, or sub-tropical regions with strong precipitation seasonality. It results in larger deviations in regions with long suitable growing seasons that allow for more flexibility in timing of agricultural operations. Moreover, the model does not consider multiple cropping systems or crop rotations, but addresses single-crop systems only. The cultivation of different crops in a sequence can nevertheless constrain the growing periods of each single crop. In temperate and continental regions, the rotations typically include both winter and summer crop types (Kollas et al., 2015). In such cases harvest and sowing of two consecutive crops are in rapid succession, leading to e.g. delayed sowing of the winter crop. However, it has been shown that there is convergence of anthesis and maturity dates of winter crops, that results in similar harvest times for crops sown several weeks apart (Hay, Porter, et al., 2006). In sub-tropical regions, long and favorable growing seasons often allow for sequential cropping systems, where two crops are grown in sequence within a single growing season. These systems can be more productive than the cultivation of the longest-growing cultivar of a single crop citepWaha2013. In the model, we account for a maximum growing period length, beyond which there is no further yield benefit (GP_{maxrp}). For future model applications, this feature could allow for using the remaining suitable growing period for a second crop cycle in the same year. We apply a crop-specific parametrization, even though differences exist not only among species, but also among cultivars or sub-species, such as Indica or Japonica rice (Sánchez, Rasmussen, and Porter, 2014). Knowledge on cultivar-specific characteristics would improve the model applicability, although to evaluate the performances of such parametrization, one would require spatially explicit datasets on cultivars, as well as on their cropping periods, which may be difficult to retrieve even at a regional scale.

The model does not account either for soil water holding capacity or any water-harvesting, or soil moisture conservation practices (Jägermeyr et al., 2016), which exist even in rainfed systems. These could be the reason for the underestimated GPs (harvest dates are simulated earlier than observations), e.g. maize in India and Mexico. Similarly, the large fraction of underestimated rice harvest dates (e.g. -3 months difference for rice panel in Fig. 3.2, Southeast-Asia and Colombia, Appendix B, Section F) may derive from different assumptions on water management in the model and MIRCA2000. This dataset assigns standard GP lengths to three classes of rainfed rice cultivation systems (7 to 8 months to upland-; 7 months to deep-water-; 4 months to paddy-rice systems). This suggests that the maximum GP that we assume in these areas is not parameterized well for rice and that a higher threshold (GP_{maxrp}) could lead to a substantial model improvement in these areas. Although such extended observed GPs might coincide with deep-water rice (flooded) (Khush, Garrity, et al., 1984), this practice is not considered in the model. Moreover, upland rice can have shorter GP (Khush, Garrity, et al., 1984) than those assumed by MIRCA2000. In the same areas, both MIRCA2000 and SAGE report secondary growing periods of rice with much shorter (3 to 4 months) durations (not shown here), which are closer to our results. To include explicit simulation of the soil water content into our modelling approach would drastically increase its complexity, and the number of simulated processes and assumptions. This would in fact require the use of a global crop-hydrological model (e.g. Schaphoff et al. (2018) with dynamic simulation of soil-plant hydrological processes and with additional input datasets on soil types, weather variables, and water management. We have shown that the end of the reported growing periods coincides respectively with a declining or peaking trends of the two simple indicators based on the P to PET ratio, that we therefore consider good indicators of dryness that can be used for large parts of the simulated land area.

Our findings show that it is generally possible to compute growing periods, defined by sowing dates (Waha et al., 2012) and maturity dates (this study) from climatic parameters. To our knowledge, this is the first study that presents a methodology to directly estimate maturity dates at the global scale, without relying on GDD computation. Note that the model should not be used for directly estimating interannual variability in crop phenology. This method provides a dataset that can be used to parametrize crop phenology without relying on any particular phenological model. It can be used to fill data gaps or to estimate cropping periods outside the current cropland as done by Elliott et al. (2015) for the sowing dates. The combination of sowing and harvest date function also allows for embedding agricultural management decisions on the cropping periods within global crop modelling approaches, where the assumption is often that farmers do not adjust to changes in growing seasons (Rosenzweig et al., 2014). Uncertainty about future climate can be accounted for by running our algorithm with different climate datasets. Under extreme scenarios it is likely that the model would not find suitable growing periods for the crops. In such case, as for the currently unsuitable regions, the algorithm would choose the shortest maturing cultivar. Moreover, the model allows for studying changes in crop sensitivity to temperature or precipitation due to breeding or to technological change, as the crop physiological limits are explicitly represented. This enables to account for autonomous adaptation in crop model simulations, but comes at the price that cultivation systems in some regions (e.g. tropics) can only be presented less well for current conditions than if sowing dates were prescribed (Elliott et al., 2015; Müller et al., 2017). The implications of this need to be tested with the model-specific parameterization of crop species and will have to be considered in the interpretation of results.

3.5 Acknowledgments

This work is part of the MACMIT project (01LN1317A), funded by the German Ministry for Education and Research (BMBF). The authors gratefully thank Frank Wechsung, as well as the members of the LandUse and LPJmL groups at PIK for their support and helpful comments; the GGCMI project for providing access to the AgMERRA dataset; the European Regional Development Fund (ERDF), the BMBF, and the Land Brandenburg for providing resources on the high performance computer system at PIK.

3.6 Data availability

Ncdf4 data files of computed sowing and harvest dates, corresponding to figures in Appendix B (Section G) are associated to this article. All other data (model input and output), as well as the R scripts used for generating the results of this study are available from the author upon request at: sara.minoli@pik-potsdam.de.

4

Global crop yields benefit from adapting phenology to future climate change

Sara Minoli[1,2,3], Jonas Jägermeyr[4,5,1], Christoph Müller[1]

[1]Climate Resilience, Potsdam Institute for Climate Impact Research (PIK), Member of the Leibniz Association, 14412, Potsdam, Germany
[2]Integrative Research Institute on Transformations of Human Environment Systems (IRI THESys), Humboldt-Universität zu Berlin, Unter den Linden 6, 10099, Berlin, Germany
[3]Albrecht Daniel Thaer-Institut für Agrar- und Gartenbauwissenschaften, Humboldt-Universität zu Berlin, Unter den Linden 6, 10099 Berlin, Germany
[4]Department of Computer Science, University of Chicago, Chicago, IL 60637, USA
[5]NASA Goddard Institute for Space Studies, New York, NY 10025, USA

Significance statement

Agricultural systems dynamically evolve in response to environmental, technological, and societal changes. The growing and wealthier global population, combined with the competition for land and other resources require agricultural productivity to increase while adapting to potentially negative impacts of climate change. As yet, many studies have focused on the pure biophysical responses of crop yields to climate change, assuming no change in management. We present new quantitative evidence that opportunities in adjusting the growing periods to new local climate can outweigh adverse climate change effects. Our results suggest that such shifts in crop growing periods could improve productivity across most of the present cropland, although not sufficient to completely offset negative impacts where conditions become almost unsuitable for agricultural production.

Abstract

Broad evidence is pointing at possible adverse impacts of climate change on crop yields. Due to scarce information about management practices and farmers' decision making, most global-scale studies, however, do not consider adaptation strategies. Here we use a global modeling framework to investigate how accounting for crop phenology adaptation affects estimates of climate change impacts on global crop production under future climate. Farmers in each simulation unit are assumed to select sowing dates and cultivars to match the crop growing periods with the most favorable climatic season. We compare counterfactual management scenarios, assuming crop calendars and cultivars to be either the same as in the reference climate or adapted to future climate. We find that, even under the assumption of unchanged management, climate-driven production losses (-13%) can be overcompensated by the CO_2 fertilization effect (+9%). However, by using decision-making rules for optimized sowing dates and cultivar choices, we are able to identify growing periods that can further increase global crop production up to +19%. Yet, most of the currently cultivated land will experience limitations to crop growth, such as too high temperatures or too dry growing seasons. The adaptation algorithm used here allows for identifying regions where these limitations can be overcome and others where they render climate change phenology adaptation very challenging. Growing period adaptation in general requires growing longer maturing cultivars. However, these might not exist yet and the adaptation potential shown here might require concerted actions of farmers, breeders and markets to provide new cultivars.

4.1 Introduction

Plant phenology is the sequence of morphological and physiological events in the annual plant growth cycle. The onset and rate of progress of phenological events are primarily driven by air temperature (and in some species by day length) and therefore the rising global temperatures due to climate change alter the timing of plants' phenology. Phenological records of the recent past in Europe (Menzel et al., 2006; Estrella, Sparks, and Menzel, 2009) show that the responses of plants to temperature increase has determined earlier and faster phenological progress of both wild and cultivated plants. Faster growing cycles associated to higher temperatures have been indicated as one of the main mechanisms of climate change impacts on crop yields (Asseng et al., 2014; Zhao et al., 2017).

However, phenology of annual crops depends also on farmers' decisions on sowing dates and varietal choice (Craufurd and Wheeler, 2009; Olesen et al., 2012; Tao et al., 2014) and it has been observed to be less responsive to historical temperature increase than the phenology of natural ecosystems (Estrella, Sparks, and Menzel, 2009; Estrella, sparks, and Menzel, 2007). Annual crops have growing period durations of usually much less than a year. They are thus exposed only to a fraction of the annual weather (Roberts, Summerfield, and Ellis, 1997), and farmers can adapt crop management practices to enhance productivity and resource use by growing crops during the most favorable season. The existence of cultivars with a broad range of maturity classes enables the geographical distribution of individual crops over large regions (Trevaskis et al., 2007; Kamran, Iqbal, and Spaner, 2014) and it is considered central for adapting cropping systems to changing climatic conditions (Kahiluoto et al., 2018).

It is of paramount importance to accurately represent growing periods and phenology in crop simulation models for estimating yield responses to climatic factors (Sacks and Kucharik, 2011). At the global scale, calibration of crop phenology to reported historical crop calendars (e.g. Portmann, Siebert, and Döll (2010) and Sacks et al. (2010)) has been shown to improve simulation of observed inter-annual yield variability (Elliott et al., 2018; Jägermeyr and Frieler, 2018). However, such static parameterizations do not allow for assessing farmers' adaptive behavior under climate change influence and therefore previous studies have assumed unchanged sowing dates and cultivar selection for climate impact assessments (Rosenzweig et al., 2014). Recent regional studies indicate that climate change impacts on crops might be overestimated when adaptive changes in management remain unconsidered. For Western Germany, for instance, Rezaei et al. (2018) found that temperature increases explain only half of the observed negative trend in heading date (timing of inflorescence emergence) of winter wheat, while recent faster-maturing cultivars account for the rest. In the U.S., maize yields have increased despite temperature increases, not least due to earlier sowing and longer-season cultivars (Butler, Mueller, and Huybers, 2018). Experimental trials show that improved wheat cultivars with delayed anthesis and increased grain filling rate (Asseng et al., 2018), or with early sowing (Hunt et al., 2019), can increase productivity under the currently warming climate.

That said, studying changes in crop phenology at global level is constrained by the lack of sufficient information on farm management. In particular, there is no comprehensive data set on crop cultivars and their thermal-time requirements (van Bussel et al., 2015). For historical studies, these can be derived from rather coarse global crop calendars (Jägermeyr and Frieler, 2018) but the assessments of future agricultural production systems typically ignore adaptation in crop phenology (Rosenzweig et al., 2014). Recently, there has been increasing efforts towards better representing farmers' decision making on crop growing periods and cultivars in crop models (Waha et al., 2012; van Bussel et al., 2015; Mathison et al., 2018; Iizumi, Kim, and Nishimori, 2019; Minoli et al., 2019).

The aim of this study is to investigate how accounting for farmers' adaptive management affects estimates of climate change impacts on global crop productivity under future climate (2080-2099). Particularly, we assess (i) how farmers could adapt crop phenology in response to climate change by adjusting sowing dates and cultivars and (ii) how climate change impacts on crop yields and production may vary under different management assumptions. We consider three counterfactual management settings, where farmers are assumed to continue applying current management practices (*unchanged management*); to promptly adapt sowing dates and cultivars to future climate (*complete adaptation*); to adapt sowing dates and cultivars, but with 20 years delay *delayed adaptation* (Table 4.1). The estimation of sowing and harvest dates is based on the methodology described in Waha et al. (2012) and Minoli et al. (2019), respectively. These are rule-based approaches that use climate statistics and agronomic principles to identify the most suitable average growing periods of major food crops in each grid cell of the model. We assume that farmers select the growing period of each crop by maximizing the time for grain growth while minimizing the risk for adverse environmental conditions, based on the long-term average temperature and precipitation seasonality. Phenological parameters (thermal units between sowing and harvest) are estimated to parametrize adapted crop cultivars for different climate scenarios. We then simulate daily crop phenology and yields under historical and future climate with the LPJmL-PHU model (Jägermeyr and Frieler (2018); additional details in Appendix C[1], Supplementary text S1) under different adaptation assumptions. We assess the effects of climate change and adaptation under four different climate scenarios from the General Circulation Models (GCMs) GFDL-ESM2M, HadGEM2-ES, IPSL-CM5A-LR and MIROC5 under the Representative Concentration Pathways 6.0 (RCP6.0) as provided by the ISIMIP2b project (Frieler et al., 2017b).

4.2 Methods

4.2.1 Modeling framework

4.2.1.1 Crop calendars and cultivar parameters

We derived location-specific cropping calendars by combining two approaches to estimate average sowing and harvest dates respectively, that are explicitly targeted to global modeling

[1]Supplementary Information for this chapter are reported in Appendix C of the thesis.

applications. Particularly, we derived both historical and future long-term average sowing and maturity (here considered to be equal to the harvest) dates following the methodologies described by Waha et al. (2012) and Minoli et al. (2019), respectively. Both are rule-based approaches in which the underlying assumption is that farmers base their decisions on the timing of sowing, on which cultivar to grow on the climatic (20-years weather) characteristics of the specific location and, lastly, on the physiological limitations of the respective crop species.

The climate is classified based on the coefficient of variation of long-term averages of monthly temperature and precipitation. In case of predominant precipitation seasonality, the preferred sowing date is assumed to occur at the onset of the wet season. On the contrary, if the most constraining factor to the growing season is temperature, the sowing date occurs when a crop-specific threshold is crossed. After determining the sowing date, as described above, the average maturity date is estimated following three main principles: 1) the crop grain filling phase, the most critical for yield formation, should occur under the least stressful conditions possible, therefore avoiding temperatures higher than the crop optima and dry period with insufficient water supply (for rainfed crops only); 2) if both temperature and water supply are limiting, the stress factor that occurs earlier triggers the end of the growing period; 3) in case of long and favorable seasons, there is no advantage in growing a crop for more than about 120 days, as thereafter the increment of the grain filling phase per additional unit of total growth time levels off.

The choice of cultivars requires two steps, first the estimation of the most suitable growing period (sowing and maturity dates as described above and in Minoli et al. (2019)) and second, the computation of the phenological thermal units (TU, °C day) required to meet the targeted maturity date on a multi-year average basis. TUs are specifically derived for each grid cell and crop from the respective climate input. They are calculated as the sum of daily mean air temperature increments above a crop-specific base temperature (see Table S1) between the sowing and maturity. Wheat phenology also considers vernalization requirements. More details on the TU calculation are presented in Jägermeyr and Frieler (2018). Obtained TUs are calculated externally and then used as model input to simulate daily phenological progress, which represent the pace of crop development from sowing to maturity as dependent on the air temperature.

4.2.1.2 Crop phenology and yields simulation

We performed a modeling experiment across the global land grid at 0.5° x 0.5° resolution. We used the LPJmL-PHU model version (Jägermeyr and Frieler (2018); refer also to Supplementary text S1) to simulate daily growth and phenological development of five grain crops (maize, rice, sorghum, soybean, wheat) and two irrigation settings (rainfed and unlimited irrigation). In the historical runs, the 20-years average crop yields have been calibrated to FAO country level statistics , by scaling the maximum Leaf Area Index parameter (LAImax, ranging from 1 to 7) which is an indicator of cropping systems intensity (e.g. fertilization inputs). The harvest index and a scaling factor that describes the relationship of leaf-level photosynthesis to field-scale photosynthesis are scaled together with LAImax as described by Fader et al. (2010).

4.2.2 Experimental design

4.2.2.1 Management settings

We investigate adaptation potentials to the end-of-the-century climate change (2080-2099) of sowing and cultivar choice, by simulating crop yields under three counterfactual management settings: (i) sowing and cultivar adapted to the 1986-2005 historical climate *unchanged management*; (ii) sowing and cultivar adapted to the 2060-2079 climate *delayed adaptation*; and (iii) sowing and cultivar adapted to the 2080-2099 climate *complete adaptation* (Table 4.1).

We run separate simulations for five different crops (maize, rice, sorghum, soybean and wheat) and two water management settings: purely rainfed and fully irrigated. It should be noted that the computed sowing dates do not differ between rainfed and irrigated crops. Hence, in water limited regions, growing periods of both rainfed and irrigated crops are starting in correspondence of the main precipitation season. In contrast, the water limitation rule for the computation of the maturity dates of irrigated crops was switched off. Therefore, irrigated-crop cycles are allowed to extend for a longer period than the rainfed crops into the dry season.

Table 4.1: Simulation protocol. Characteristics of management assumptions and climate inputs for four simulation setups run for each climate scenario. Sowing and harvest dates are calculated based on the climate of the respective time period and cultivar thermal unit requirements are computed as described in the methods for three different time slices.

ID	Management settings		Crop model simulation time period	
	Sowing dates and cultivars	Sowing and cultivar adapted to time period		
1	Reference	1986-2005	Historical	1986-2005
2	Unchanged management	1986-2005	Future	2080-2099
3	Delayed adaptation	2060-2079	Future	2080-2099
4	Complete adaptation	2080-2099	Future	2080-2099

4.2.2.2 Historical and future climate data

We used climate forcing and CO_2 mixing ratios datasets from the ISIMIP2b protocol (Frieler et al., 2017b). These include bias-adjusted climate input data from the CMIP5 project (Taylor, Stouffer, and Meehl, 2012) at daily temporal resolution and 0.5° horizontal resolution for historical and future conditions. We used data of four individual General Circulation Models (GCMs), namely GFDL-ESM2M, HadGEM2-ES, IPSL-CM5A-LR and MIROC5 under the Representative Concentration Pathways 6.0 (RCP6.0) of three 20-years long time slices: 1986-2005, 2060-2079 and 2080-2099.

4.2.2.3 Data processing and analysis

We assess the future adaptation potentials over the present-day cropland. We use the MIRCA2000 dataset (Portmann, Siebert, and Döll, 2010) that reports crop-specific area separating for rainfed and irrigated crops at 0.5° resolution. We refer to the crop-specific total area, summing up the area of all individual cropping periods (so-called "subcrops").
To quantify the performances of cropping systems we compute grid-cell level 20-years average crop yields in each simulation period and GCM. In addition, we compute the total calorie production of all crops as the area-weighted sum of their calories content (formula and parameters as in Minoli et al. (accepted for publication), see Chapter 2).
To assess climate change impacts under different management assumptions, we compute the yield and production changes between the future (2080-2099) and the reference time period (1986-2005). Moreover, in order to isolate the management effects from the climate effects, we compare the yield differences between contrasting management scenarios under the same future time period (2080-2099). We account for uncertainty due to climate scenario by expressing the evaluation metrics of crop area and yields as the mean and range across the four GCMs, while patterns of categorical variables are described reporting the number of GCMs for which a certain pattern is observed. Global maps of categorical variables are shown for one GCM only as an example as these cannot be averaged meaningfully.
We define crop cultivars based on the phenological TUs (°C days) required to reach maturity. As a measure of future cultivar availability, we consider the distribution of TUs under different scenarios.

For data processing we used R (R Core Team, 2018) and R-packages for handling netcdf4 (Pierce, 2015), performing computation (Dowle and Srinivasan, 2017; Wickham, 2011) and plotting results Wickham, 2009.

4.3 Results

4.3.1 Reference growing periods and cultivars

Thermal unit requirements can be interpreted as crop cultivar maturity classes. To derive cultivar global patterns, we computed locally-adapted sowing and maturity dates from climate data and then estimated the phenological thermal units required to reach maturity (TUs, °C day) under that climate. Cropping calendars that have been computed in the reference time period (1986-2005) are found to represent with good approximation the patterns reported by observational datasets, which are representative for the year 2000 (Portmann, Siebert, and Döll, 2010) (Fig. S1-S3). We therefore assume that the corresponding TUs give a plausible representation of the cultivars grown in that period. The computed TUs (Fig. 4.1 and Fig. S4) show large variation for each individual crop, with interdecile ranges (10^{th} and 90^{th} percentiles) from about 1370°C days (maize) to 2900°C days (wheat) (excluding the area where the shortest maturing cultivars are selected). This illustrates the vast phenotypic resources that allow for grain crops adaptability across very diverse climates. Moreover, within these ranges, each crop shows a different distribution of cultivar maturity classes (Fig. 4.1), in which the more extreme classes (very short or long maturing cultivars) are found to cover smaller shares of the current cropland of the five crops considered here (630 Mha) (Portmann, Siebert, and Döll, 2010) .

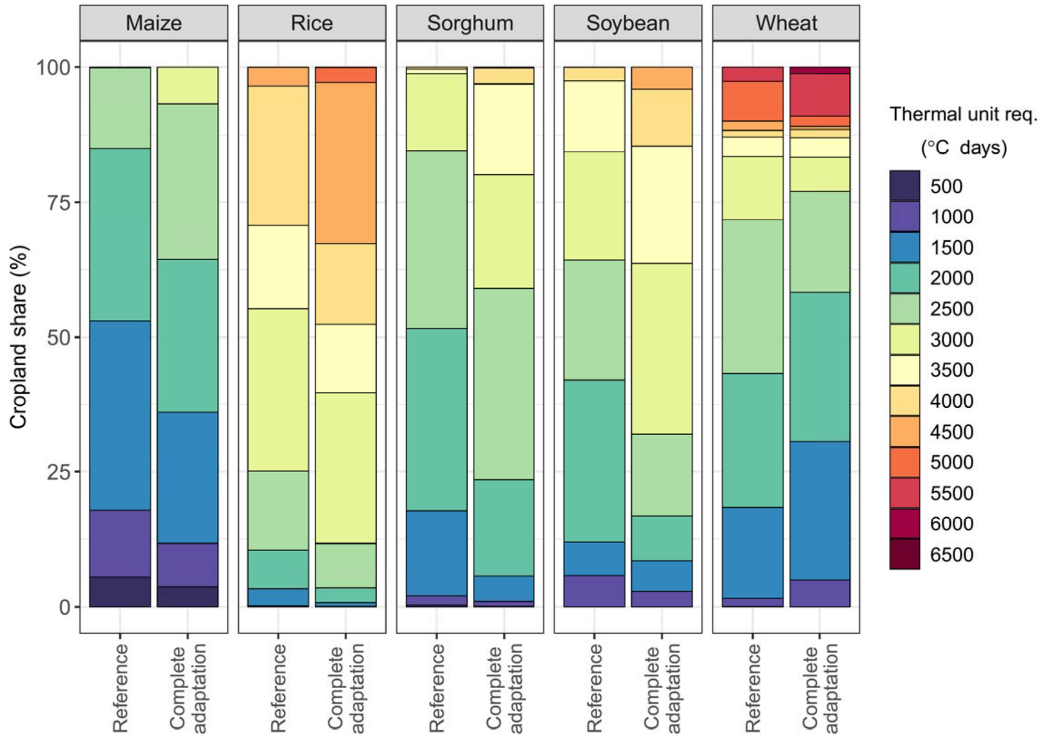


Figure 4.1: Crop cultivars distribution across the global cropland under *reference* (1986-2005) and *complete adaptation* (2080-2099) scenarios. The bars display cropland shares (%) to which classes of cultivars are assigned. Cultivars classes are represented by intervals of thermal unit requirements (TUs) to reach maturity. TUs ares computed under the respective climate and growing periods. Grid cell level thermal units represent the mean across GCMs. Grid cells where the adaptation algorithm cannot find a suitable growing period, therefore selecting the shortest maturing cultivar (GPmin) are excluded.

4.3.2 Growing periods and cultivars under future climate

In the first set of future simulations, (*unchanged management* scenario) we assess what would happen if farmers did not take any action in response to climate change and continued applying the current agronomic practices (sowing dates and cultivars) under 2080-2099 climate. This scenario is unrealistic, but it is a typical assumption in climate change impact studies (e.g. Rosenzweig et al. (2014)). Even though sowing dates and cultivars remain the same as the historical ones (not shown as curves of *reference* and *unchanged management* in Fig. 4.2A,B perfectly overlap), we find an overall decline in growing period durations (Fig. 4.2C). This is a consequence of increased temperatures that determines faster accumulation of thermal units and thus advancement in maturity dates.

In the *complete adaptation* scenario, we assume farmers to adapt sowing dates and cultivars to future climate (2080-2099, RCP 6.0). According to the agro-climatic classification applied here, we find that future global patterns of temperature and precipitation seasonality do not substantially change. About 88.6[86.0,91.2]% of the area do not change in seasonality class (mean[range] across GCMs) (Fig. 4.3B and Fig. S5B-S7B).

Consequently, in most regions, future sowing dates are determined based on climatological factors similar to the historical ones (Fig. 4.3A). In the temperate zones, sowing dates remain temperature driven, depending on the onset (or cessation for winter wheat) of the warm season. Due to an earlier spring onset, temperature dependent sowing dates of all crops (except winter wheat) occur earlier than in the reference scenario (on 52.8[51.0,54.6]% of the cropland sowing dates advance of more than seven days). As opposed, in the sub-tropics sowing dates remain precipitation driven to capture seasonal water availability and appear relatively constant (only 26.1[21.6,32.6]% of the area shows changes larger than seven days), indicating that the timing of the wet season is projected to have little variation in these particular climate scenarios (Fig.S8).

Despite small changes in seasonality types we find an overall increase in growing season temperature levels. Particularly, the share of current cultivated area subject to temperatures exceeding crop-specific optima for yield formation (see Minoli et al. (2019)) increases from 66.8[64.8,68.8]% (Fig. 4.1C) to 91.2[84.2,95.7]% (Fig. 4.1D) in the reference climate scenario and at the end of the century, respectively (mean changes across GCMs). Note that “high temperatures” refer here to long-term monthly averages, which do not represent abnormal extreme heat events, but rather long periods of continuously high temperatures within the year. We assume that the farmer considers those as usual weather conditions, demanding for adjusting the choice of adequate cultivars.

We find that cultivars adapted to future climate generally require more TUs (Fig. 4.1 and Fig. 4.2B). Wheat is an exception as adapting winter wheat to higher temperatures requires both delaying sowing and advancing harvest (Fig. S8 and S9). It is evident that cultivars that are currently only marginally in place, and thus covering small land shares, may become very prominent under future scenarios. Due to higher global temperatures, the increase in TUs will be necessary. Nevertheless, we find that adapted growing periods are shorter than in the reference in some areas. The duration of the adapted growing periods is similar to the reference growing periods (median close to zero), but the distribution of the differences shows that the adaptation algorithm selects both longer and shorter growing periods (Fig. 4.2C), resulting in a scattered picture of variation in growing period lengths (Fig.S9).

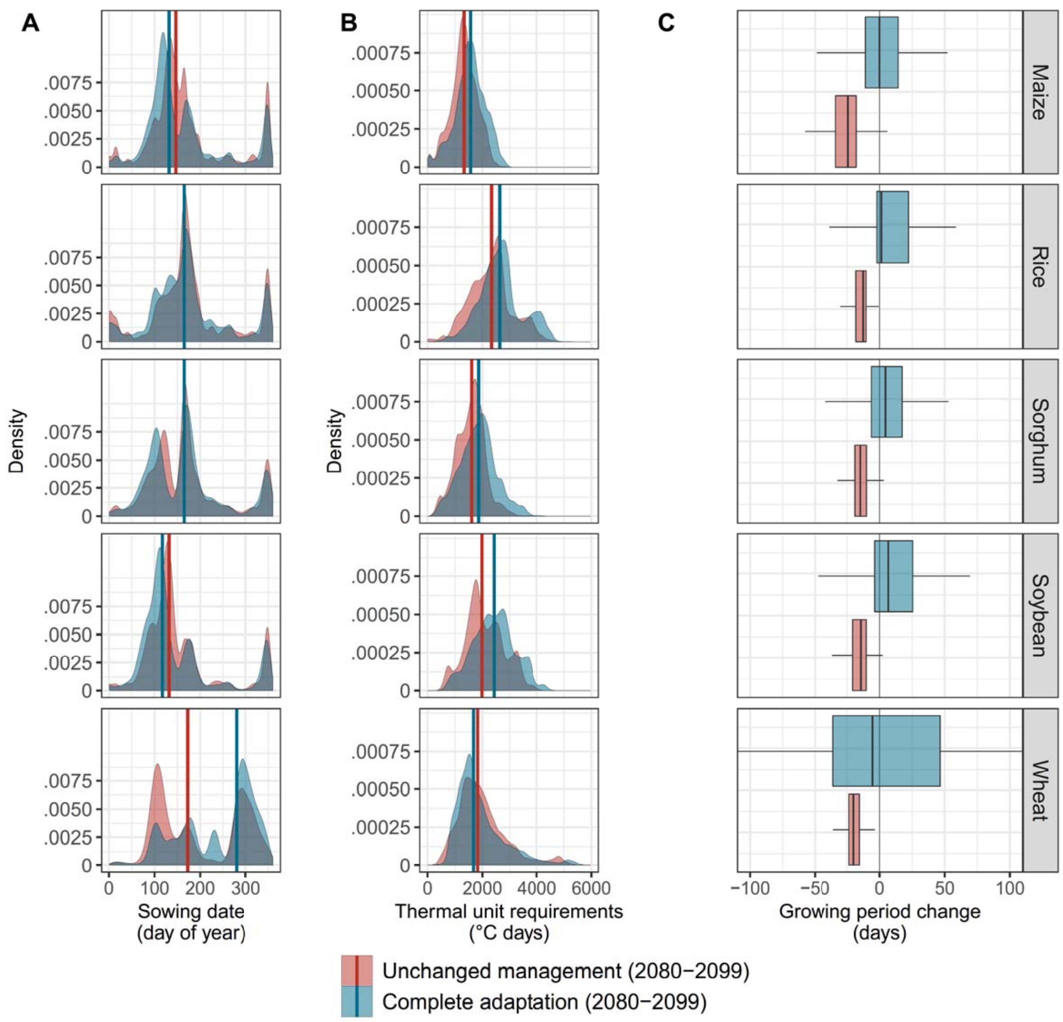


Figure 4.2: Climate change effects on sowing dates, cultivars and growing periods under different management assumptions for the five crops. Kernel density plots of grid-cell level (A) sowing dates, (B) thermal unit requirements and (C) boxplots of growing period change from the reference scenario are displayed for individual crops and management assumptions, each including all grid cells of both rainfed and irrigated cropland. Values in each grid cell are averaged across the four GCMs. Colors indicate the management setting: unchanged management (red) and complete adaptation (blue), respectively. In the kernel density plots, for an interval of values on the x-axis, the area underneath the curve indicates the probability density of those values; for the full x-axis range the area equals one.

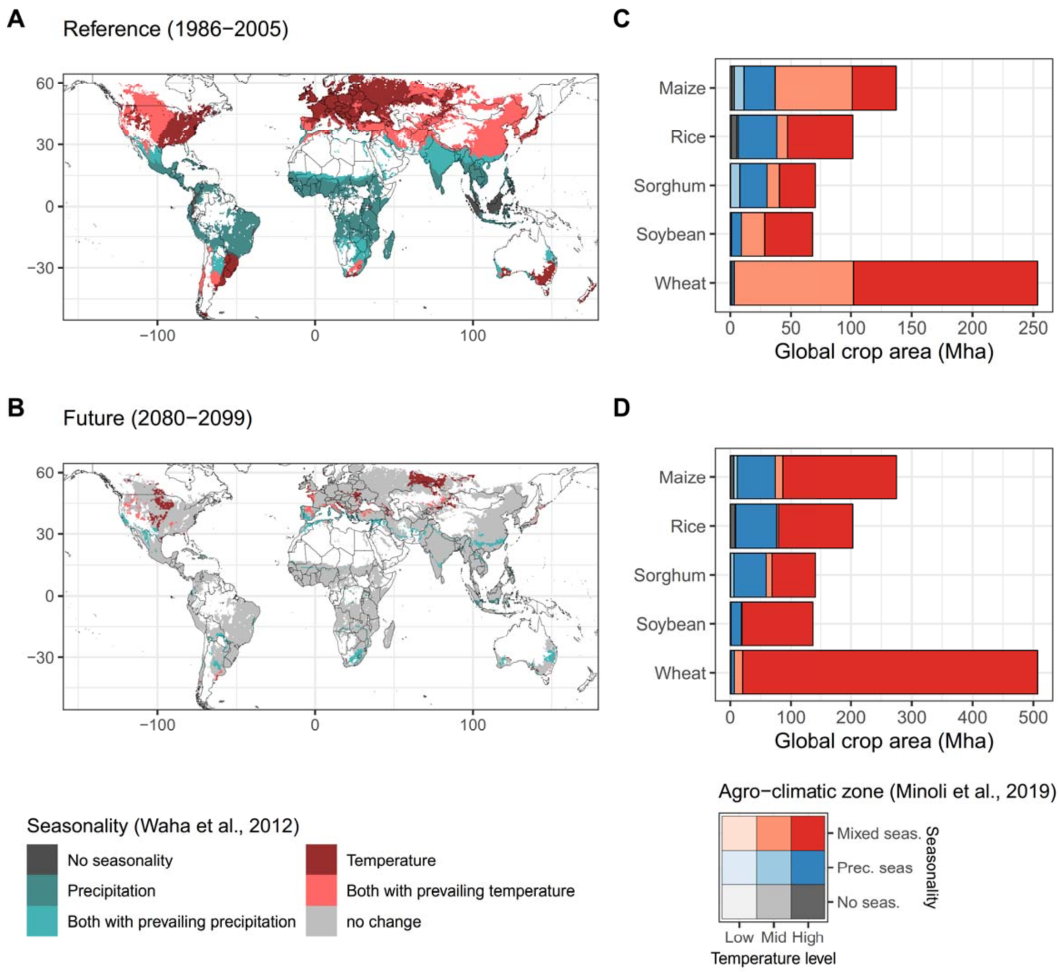


Figure 4.3: Seasonality and agro-climatic zones under reference and future climate. Panel (A) displays the seasonality types under historical climate (1986-2005). Panel (B) shows changes by 2080-2099 (RCP6.0) through highlighting the updated class in regions of change only. Seasonality classification is based on the main climate limitation to crop sowing dates in each grid cell Waha et al. (2012). Panel (C) and (D) display the global cropland area allocated to different agro-climatic zones under reference (1986-2005) and future climate (2080-2099, RCP6.0). "No seasonality" refers to low seasonal variation in both temperature and precipitation; "Precipitation seasonality" is where precipitation dominates seasonality, and "Mixed seasonality" covers both regions with temperature as dominant factor regions with temperature and precipitation seasonality. "Temperature level" refers to the temperature of the warmest month compared to crop-specific thresholds relevant to yield formation, where "Low" means that monthly temperature is always below the minimum level; "Mid" that temperatures are between the minimum and the optimum; "High" that temperature of the warmest month is higher than the optimum. Cropland masks are based on MIRCA2000 (Portmann, Siebert, and Döll, 2010). This figure shows results based on the HadGEM2-ES GCM as one example, other GCMs show generally the same patterns (see SI).

4.3.3 Adaptation effects on crop production

Globally, the effects of climate change on total crop calorie production (Peta calories = 10^{15} calories) appear positive, even in absence of adaptation measures. Under *unchanged management*, despite the shortening of the crop growing periods due to accelerated phenology Fig. 4.2, production increases by +9.2[4.9,11.8]% (dark red bar in Fig. 4.4A, all crops). These positive effects are largely due to CO_2 fertilization. C_3 species (rice, soybean and wheat) are indeed much more responsive than C_4 species (maize and sorghum) to increased CO_2 concentration (dark red bars in Fig. 4.4A, single crop panels). Furthermore, under the counterfactual scenario with *static* CO_2 fixed at the baseline level, total production is decreased by -13.2[-17.5,-9.9]% (light red bars in Fig. 4.4A, all crops). The impact is consistently negative for each crop and almost everywhere on the current cropland (bottom-left panel in Fig. 4.4B). The spatial patterns reveal that differences exist in CO_2 fertilization effects across regions. For instance, climate change impacts in large areas within the subtropics remain negative, although they are slightly alleviated by increased CO_2 (top-left panel in Fig. 4.4B).

Altogether, our results show that growing periods and cultivars, as computed by the rule-based approach, can be an effective adaptation measure to climate change. Under *complete adaptation* and *dynamic* CO_2, total crop calories production increases by 19.0[13.6,22.3]%, showing positive effects for all five crops (dark blue bars in Fig. 4.4A). Spatial patterns indicate that adaptation helps exploiting the beneficial effects of CO_2 fertilization, especially in temperate and arid zones. Additionally, across large portions of the subtropical regions, adapted growing periods turn negative production changes into positive ones (top-right panel in Fig. 4.4B). The counterfactual scenario with *static* CO_2 proves the potential of growing period adaptation, which can globally alleviate production decline (-4.2[-9.0,-0.7]%, 9 percentage points less than without adaptation) (Fig. 4.4A). Compared to the *unchanged management* scenario, climate change impacts are still persisting in many grid cells, yet they are generally lower, neutral or even positive under this scenario. The effects of adaptation in the tropics appear more beneficial than those of CO_2 fertilization (bottom-right panel in Fig. 4.4B). Being growing periods adjusted to capture more seasonal precipitation in these regions, the effect might indicate that here crop growth is limited more by water than by CO_2.
Under the *delayed adaptation* scenario we assume that sowing and cultivar adapted to the 2060-2079 climate are used under the 2080-2099 climate. We find that *delayed adaptation* (green boxes in Fig. 4.4A) is slightly less effective than *complete adaptation* in 2080-2099, indicating that the adaptation algorithm consistently captures the more favorable conditions for the specified time period. Overall, these results point at the drastic overestimation of climate change impacts on crop production that might occur if sowing dates and cultivars are assumed to remain unchanged under future climates.

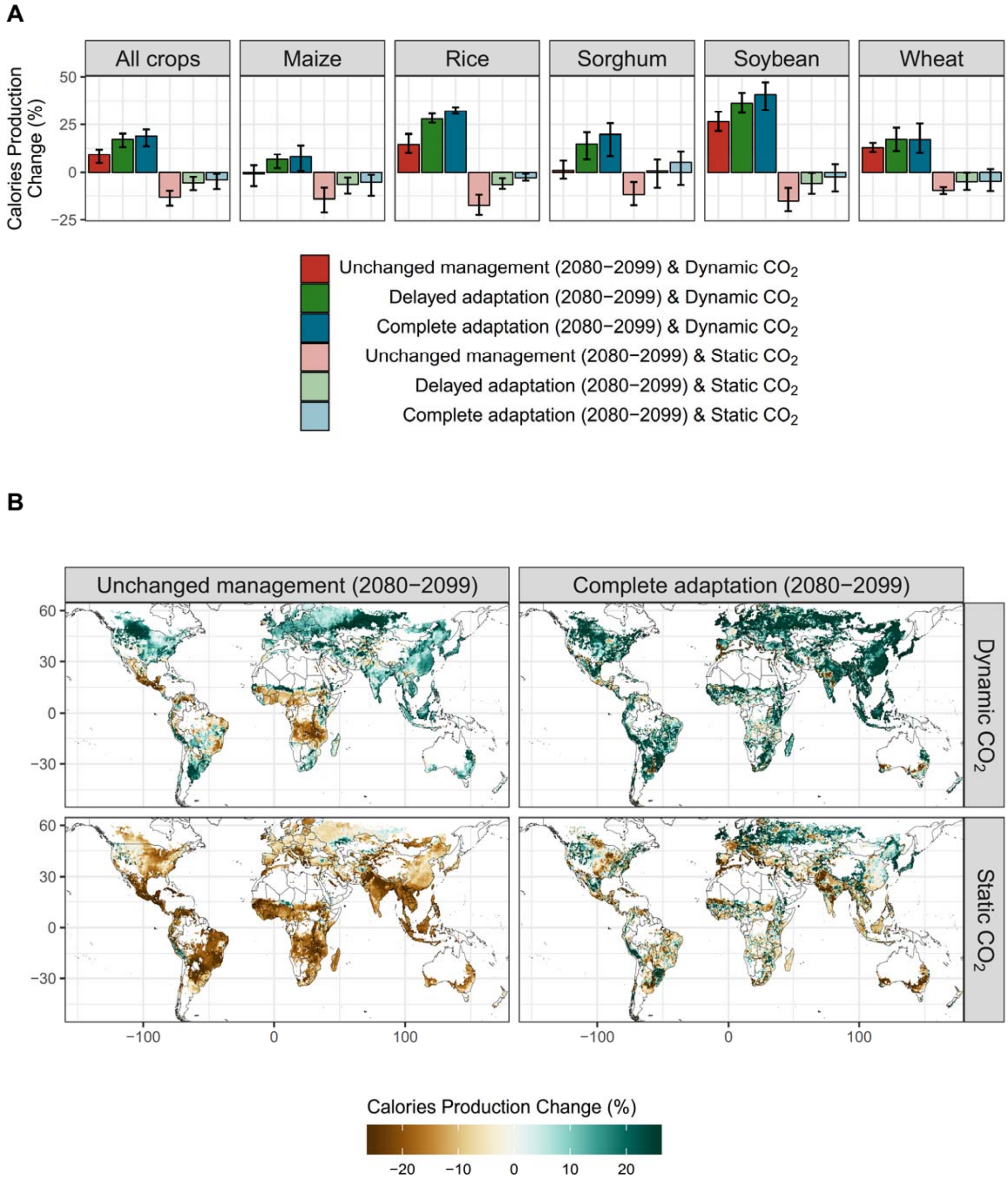


Figure 4.4: Effect of climate change on crop calories production assuming different CO_2 and management settings. Calories production of individual crops at the grid-cell level is computed as the product of crop-specific grain yield, calories content and harvested area. The change is computed as the relative difference (%) between production in the future (2080-2099) and in the reference time period (1986-2005). (A) Relative change of global calories production shown for both all crops and each individual crop. (B) Relative change of grid-cell level production of all crops. The bars and segments represent respectively the mean and the range across four GCMs.

4.3.4 Isolating management effects on crop yields

In order to isolate the management effects from the climate effects, we compute the difference between adapted (*complete adaptation*) and non-adapted (*unchanged management*) yields under the same future time period (2080-2099). We find that the difference is generally positive (Fig. 4.4A). Particularly, for maize, rice, sorghum, soybean and wheat respectively, median absolute yield changes are 0.29, 0.40, 0.09, 0.21 and 0.02 Mg ha^{-1} (Fig. 4.4A), which correspond to median relative changes of 17.2, 14.3, 13.8, 14.5 and 1.7 %. Overall, changes reported in absolute terms appear small. It should be noted that, impact assessment studies usually report relative yield changes (%) only. We believe that reporting yield changes also in absolute terms (Mg ha^{-1}) gives a more robust picture. In fact, relative changes tend to emphasize small differences occurring on less productive areas or crops, whereas absolute changes somewhat distort the comparison across crops, because 1 Mg ha^{-1} of change can be a huge difference for generally low productive crops and vice versa. Moreover, although small in absolute terms, yield changes at the grid level can substantially affect total production at the global scale (Fig. 4.4). Furthermore, differences of 1 Mg ha^{-1} in long term average yield can be relevant for producers also at the farm level (Karapinar and Özertan, 2019).

We find that almost all realized harvest reasons, show median positive effects on yields (Fig. 4.5A), indicating that the different strategies to select adapted cultivars in fact help in capturing the seasonal temperature and water resources. Yet, we also find some apparent "maladaptation" cases, where the adapted growing periods have adverse yield effects. These are mostly occurring in areas where the rule finds strong limitations to crop growth, such as too high temperatures or too dry growing seasons, and it selects the shortest maturity cultivars (light green boxes in Fig. 4.5A). Particularly, we find that the negative yield changes occur especially where there is a switch to the shortest growing period, while the yield response is positive in areas where the shortest maturing cultivar was chosen both in the reference and in the future scenario (Fig. S10). Note that the areas in which this effect occurs represent a relatively small share of the total area of each crop (light green boxes in Fig. 4.5B).

4.4 Discussion

In recent years an increasing number of studies on agricultural systems under climate change have shifted the focus from considering impacts only to adaptation strategies assessments (Porter, Howden, and Smith, 2017). Still, at the global scale the scarcity of information on crop management and its temporal evolution is challenging the implementation of adaptation scenarios in crop models (Challinor et al., 2014). Many studies indicate that current farming practices such as growing periods and cultivar choice are the result of more or less gradual adjustments and optimization of the cropping systems (Vasey, 2002; Parent et al., 2018; Kahiluoto et al., 2018; Karapinar and Özertan, 2019) carried out by both farmers and extension services over centuries and decades. Here we present a first application of agronomic rule-based approaches to project current farmers' decision-making rules on sowing dates and cultivar selection into future scenarios. Additionally, we assess the resulting effects on yields of five major staple crops on the present global cropland.

Adaptation in growing period management alone can increase global crop production by 10 percentage points (difference in production change between *complete adaptation*) and *unchanged management*). Although negative climate change impacts cannot be fully compensated everywhere, we find that phenological adaptation reduces differences among regions, especially between temperate and tropical regions, as also reported by Aggarwal et al. (2019). Some of this adaptation will be implemented by the farmers alone as they

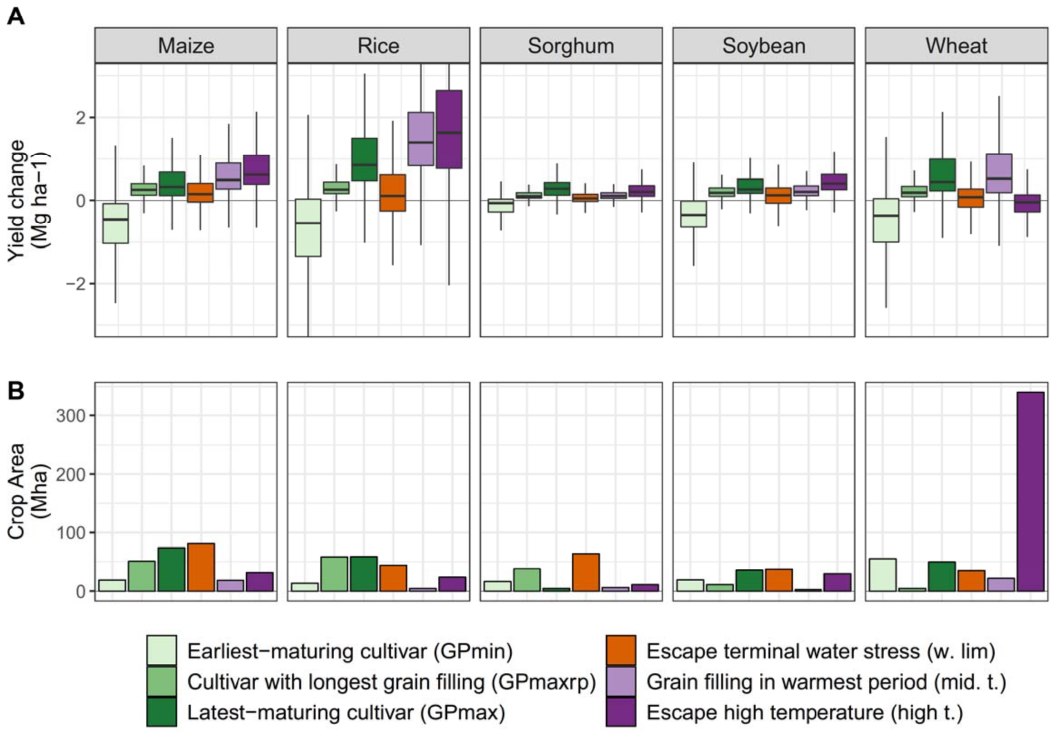


Figure 4.5: Isolated management effects on crop yields. The management effect on yields (panel A) is computed as the difference between *complete adaptatation* and *unchanged management* scenarios under the same future climate (2080-2099). The colors indicate the realized harvest reason under *complete adaptatation*, which according to Minoli et al. (2019), is the agronomic factor defining the most suitable growing period length in each grid cell. The number of data points of all boxes within each crop is given by the number of crop-specific cropland grid cells, times the four GCMs. Boxes in panel A display the interquartile range, horizontal lines depict the median value. Whiskers extend to the maximum and minimum value within 1.5 time the interquartile range. Outliers outside this range are not shown. Panel (B) displays the total crop area corresponding to the grid cells of each box in the panel above.

will also observe changing conditions and will simply respond to these as good as they can, e.g. by changing sowing dates (Karapinar and Özertan, 2019). New cultivars will, however, require concerted action of farmers (selecting), breeders (creating) and markets (providing). Even if cultivars with similar TU requirements as cultivars elsewhere exist already, it is questionable whether these can be directly transferred between regions. Differences in day length requirements might hamper phenological adaptation across latitudes (van Bussel et al., 2015; Pugh et al., 2016). Whilst, in regions with functional markets, breeders work to provide cultivars adapted to the farmers' needs (Voss-Fels et al., 2019), in others, the predominance of on-farm seed production systems can limit the introduction of new cultivars (Singh, Prasad, and Reddy, 2013). Exploiting the full growing season adaptation potential will thus depend on functional, fair, and sustainable markets in less developed regions, including the infrastructure necessary for providing those markets (IFPRI, 2009).

Our results demonstrate the importance of accounting for farmers' decision making in bio-physical modeling of climate change impacts on crop yields. Apart from crop models' tendency to overestimate the effect of growing season response to warming (Zhu et al., 2019), an assessment that is based on static sowing dates and cultivar choice helps to understand how crop growth is affected by changing climatic conditions. Such an assessment, however, does not provide information on how future agricultural production systems will be affected by climate change (Minoli et al. (accepted for publication), see Chapter 2). With new methodologies to assess changes in growing season management (e.g. Waha et al. (2012), Iizumi, Kim, and Nishimori (2019), and Minoli et al. (2019), see Chapter 3), climate change scenarios can now be supplemented with scenarios on growing season management in model experiments such as AgMIP (Rosenzweig et al., 2014; Elliott et al., 2015) and ISIMIP (Frieler et al., 2017b). This constitutes an important first step in modeling agricultural systems rather than just crop growth under climate change scenarios.

Our findings on future adapted crop cycles are in line with previous studies which have focused on Europe. Particularly, earlier sowing of maize has been found to be effective for adaptation by Dobor et al. (2016), Zimmermann et al. (2017), and Parent et al. (2018). For winter wheat we find later sowing dates, which is in agreement with Dobor et al. (2016) and Glotter and Elliott (2016), but not with Zimmermann et al. (2017) and Ruiz-Ramos et al. (2018). On cultivar adaptation, our results support others' findings from Zimmermann et al. (2017), Ruiz-Ramos et al. (2018), and Parent et al. (2018) that find benefits in using longer maturing cultivars, especially in cooler and wetter regions, as opposed to the benefit of using shorter cycles in South-western Europe and in Mediterranean regions (Fig. S11), in order to escape terminal water stress (spring sown crops) or high temperatures during grain filling (winter wheat). Yet, this latter strategy can at times result in lower yields (Fig. 4.4A, wheat) demanding for breeding towards stress-tolerant cultivars (Semenov et al., 2014). Rezaei et al. (2018) found a decline in TUs of modern winter wheat cultivars, released in Germany after 1960s. Under future climate, our simulations suggest an additional decline of TUs in those regions where winter wheat was selected also in the reference scenario (Fig. S11).

The rule-based adaptation algorithm used here considers long-term averages of temperature, precipitation and evapotranspiration. It therefore selects sowing dates and cultivars based on usual weather conditions of a given location. We do not consider short term adjustments of practices that are likely to occur on a yearly base, such as the inter-annual variability of sowing dates to match variable spring- or rainy-season onsets. On the other hand, we consider an inter-annual variability of maturity dates, as the rate of phenological progress varies according to the yearly temperature profile. It should also be noted that our adaptation algorithm does not consider the occurrence of extreme weather conditions, although these are expected to become more frequent in the future (Gourdji, Sibley, and Lobell, 2013; Deryng et al., 2014). Similar to Asseng et al. (2018), our adaptation rules for spring-sown crops escapes temperatures above the crop optima for yield formation by delaying anthesis. It does not, however, consider the possibility that extreme temperatures, potentially damaging the crop, might occur in the previous vegetative phase. Yet, also the LPJmL-PHU model, as the majority of currently state-of-the-art crop models, does not explicitly simulate heat stress effects (Rezaei, Siebert, and Ewert, 2015), although some might be implicitly captured (Schauberger et al., 2017). Further adaptation rules might need to account for additional stress factors, such as the return time of crop specific critical temperatures (Hatfield et al., 2011a; Gourdji, Sibley, and Lobell, 2013) or droughts (Daryanto, Wang, and Jacinthe, 2017) that could permanently damage the crop and reduce the final yield.

Previous studies (Rezaei, Siebert, and Ewert, 2017) found that trends in crop phenology are crop specific as farmers might take different factors into account that we do not consider here, such as the availability of cultivars with different improved traits (e.g. early flowering cultivars, longer grain filling phase, higher planting densities). One limit of our study is that we apply the same general rule (although differently parametrized for each crop) for adaptation of all crops. This is a simplification due to the global scale of the study, where we lack information on cultivar breeding trends, and therefore assume global values for physiological parameters. Moreover, the big data gap about the phenological stages between sowing and harvesting, such as canopy development and flowering time, constrain our ability to assess the effects of such improved traits.

We finally assessed the effect of contrasting management scenarios on yields. The representation of yield responses to weather fluctuations in process-based crop models is uncertain and can be improved by more accurate input data on farming management including parametrizing phenology (Elliott et al., 2015; Frieler et al., 2017a; Elliott et al., 2018; Jägermeyr and Frieler, 2018). The approach applied here is capable of reproducing historical cropping calendars based on climate data. The same decision-making rules under future climate scenario on present cropland can be effective in reducing negative impacts or even exploiting more favorable conditions, supporting the recent findings from Zimmermann et al., 2017 and Parent et al., 2018. Yet, the rule-based approach applied here is only one of the possible strategies that can be used in the future. The adaptation potential should be assessed by integrating biophysical with socio-economic aspects, e.g. land use change and technological progress, that can have much larger effects than the biophysical ones, such as climate change and management (Zimmermann et al., 2017; Iizumi, Kim, and Nishimori, 2019; Leng and Huang, 2017; King et al., 2018). The growing season rules of Minoli et al., 2019 can also be extended to assume new cultivars that have, e.g., different sensitivities to drought or heat so that scenarios on technological development can be accounted for.

The adaptation algorithm applied in this work allows for determining the most constraining climatic and physiological factors to crop growth that can limit the sowing and harvest time windows in each location. This can help identifying both the locations and the underlying reasons that render adaptation to climate change more challenging. Particularly, we could identify (i) the area that will require the use of extreme crop cultivars; (ii) growing periods that will include high temperatures, likely more prone to experience heat stress; (iii) areas where the adaptation algorithm cannot find a suitable growing season, therefore choosing the shortest maturing cultivar. Here, our results indicate that the switch to the shortest growing season is too drastic, as we found maladaptation to occur in many of these cases. Future studies could then focus on such regions to further explore adaptation options, specific to those growing conditions. This final finding is in line with Pugh et al., 2016 which find that in the future, increasingly large areas of the current cropland have no climate analogues with past climate, which could lead to substantial shifts in land-use patterns.

Future research will have to advance on the integration of bio-physical responses to changing environmental conditions, such as climate change, and socio-economic decision making. We here demonstrate the importance of farmers' decision making that is only driven by their experience of climate conditions. This can now much better inform economic modeling on future growing conditions than assessments that merely look at static growing season management (e.g. Müller and Robertson (2013)). Moreover, the presented work could become the basis for other decision making on, e.g. priced inputs, such as fertilizers (e.g. Popp et al. (2017)), irrigation water (Bonsch et al., 2015) or research (Dietrich et al., 2014). Human decision making needs to be the next focus in modeling agricultural systems under climate change. We here demonstrate the importance of accounting for decision making in growing season management. The relatively simple, purely climate-driven rules can be advanced by including more socio-economic aspects, such as access to varieties and labor during adapted planting seasons. However they help to break the lock on working with static growing season assumptions.

4.5 Acknowledgments

S.M. and C.M. acknowledge financial support from the MACMIT project (01LN1317A) funded through BMBF (Germany). J.J. received funding from the Open Philanthropy Project with partial support from the U. Chicago RDCEP center (NSF grant #SES-146364).

5

General summary and conclusions

5.1 Synthesis

Atmospheric composition and climatic conditions are of vital importance for terrestrial plants. In consequence, changes in CO_2 concentration, temperature and precipitation, as projected for a continuation of current trends, are posing a risk to cropping systems across the world. The productivity of future cropping systems depends on their resilience to climate change, which is their ability to absorb disturbances and reorganize so as to persist under changing conditions (Walker et al., 2004). The capacity of systems to adapt is an essential property for maintaining resilience (Folke et al., 2010). With an agro-ecological modelling approach this thesis explores options to adapt globally cultivated staple crops to climate change. Specifically, the focus is on the importance of crop phenology in response to climate change and on its management by varying growing periods and cultivars. The thesis is guided by the overarching research question: "Can global cropping systems be adapted to climate change by managing crop phenology?" Being the key driver of crop phenology, temperature is the main climatic variable considered throughout the three central chapters, complemented by exploring its interactions with precipitation and changes in atmospheric CO_2 concentration. The central metric for the evaluation of crop performance is the yield, which is of crucial importance for agronomists, who aim at optimizing the harvested product per unit of land. Additionally, because the energy content of food is central for human nutrition (Willett et al., 2019), yields are converted into their calorie equivalents. Calorie yields are further converted into calorie production (the product of calorie yield and cropland area), to aggregate and weight yields across different crops and spatial scales, as commonly done in studies that address land use, food security, and trade of agricultural products (Elliott et al., 2014; Müller et al., 2015; Popp et al., 2017).

5.1.1 Does maintaining today's growing periods help to mitigate negative impacts from global warming?

Chapter 2 presents results from an ensemble of seven Global Gridded Crop Models. These have been used to quantify the impacts of temperature increase on the productivity of major grain crops and their adaptation potential under different management assumptions. In order to evaluate adaptation measures that are specifically targeted at counteracting warming-induced yield reductions, the modelling experiment is designed to isolate the effect of temperature from that of CO_2 and precipitation changes.

Assuming no land use change and no adjustment in crop management, aggregated global production is estimated to decline linearly with temperature increase, resulting in a 30% loss of calories produced at 6 K of warming. Phenology is shown to be a key mechanism of temperature impacts. In more than two thirds of the simulated locations, decreasing yields are associated with a shortening of the growing periods. This effect can be avoided by using new cultivars with adapted phenology that maintain the original growing period length under each tested level of warming. This measure would fully compensate global warming-induced losses of calorie production up to 2 K of temperature increase, whereas losses compensation would be only partial at higher temperature offsets. For some crops and regions, maintaining today's growing periods under increasing temperature even amplifies the negative impacts, as it would expose crops to more severe water stress. Moreover, results of this study show that irrigation has the potential to aid phenology management in maintaining crop production above the baseline level up to high degrees of warming. Yet, it is argued that converting crops from rainfed to irrigated cannot be considered as 'true adaptation', because it does not directly reduce negative temperature effects. Conversely, irrigation is recognized to have large intensification potentials, with +20% of global calorie production in the ideal case of unlimited water availability. In practice however, exploiting this potential will only partially be feasible under climate change, as a result of decreasing water available for irrigation, especially in already water-scarce areas (Elliott et al., 2014). On the other hand, Elliott et al. (2014) find that water supply might increase in regions with already large shares of irrigated cropland, allowing for further expanding irrigation in these areas. Interestingly though, the increase in water supply found in their study is partially attributed to the shortening of crop growing periods. Therefore, it should be expected that this potential for expanding irrigation would be lost if combined with cultivar adaptation, which in Chapter 2 is the scenario showing the highest potential for reducing crop production losses. Given the scarcity of such an important determinant for agricultural productivity, improved water management is imperative. Irrigation expansion should therefore be complemented by measures that enhance crop water use, such as switching to more efficient irrigation systems, as well as optimizing the use of precipitation water in rainfed systems (Jägermeyr et al., 2016).

Chapter 2 puts emphasis on the capacity of phenology management as a measure to counteract the temperature impacts on crop productivity. Yet, it also shows that a simple one-size-fits-all measure would not serve the purpose of adapting crop production in all regions globally. Therefore, such simplified approach is not sufficient to describe realistic adaptation measures in global crop modelling studies and to understand the potential of phenology-based adaptation. Tailoring phenology management to local conditions requires a deeper understanding of the underlying drivers and processes, before dynamically implementing phenology-based adaptation into global crop models.

5.1.2 What are the main drivers and decision-making rules that determine global patterns of grain crop phenology?

The parametrization of crop cultivars and their phenology in global crop models has been a challenge for long. Although global datasets on crop growing periods have allowed advancements in global-scale crop model simulations (Elliott et al., 2018; Jägermeyr and Frieler, 2018), there is a knowledge gap in how these could evolve under climate change. Simplified approaches, as the one presented in Chapter 2 have proven to be effective for disentangling the different effects of climate change on crop growth along with systematically assessing a limited set of adaptation strategies. Yet, they are inadequate in accounting for local differences that require multiple adaptation measures, such as shifting sowing dates, selecting longer or shorter maturing cultivars and adjusting the timing of sensitive growth phases.

Chapter 3 proposes to formalize agronomic thinking in order to simulate how farmers make decisions on crop growing periods, based on local climatic conditions. This study builds on previous work conducted by Waha et al. (2012), that defined globally valid rules to estimate locally-adapted sowing dates for different crops. Here, a novel approach is developed to estimate the timing of harvest. Given the crop sowing date and climatic conditions of the area under cultivation, the algorithm seeks a suitable harvest date by matching crop physiological requirements with the climate seasonal profiles.
The main finding is that current phenology of grain crops can be largely explained by globally uniform rules. In fact, farmers' seasonal decisions appear to be driven by analogous agro-ecological factors in most locations and for all explored major grain crops. Particularly, farmers adapt sowing and harvest dates to grow crops under the best available weather conditions. Each crop is characterized by specific ranges of temperature that allow for optimizing biomass growth and yield formation and that differ by phenological phases. In order to optimally use available resources, sowing is carried out as soon as the growing season factors allow the crop to establish and grow (Waha et al., 2012). The timing of the crop reproductive phase is crucial in defining the duration of the crop cycle. Crops are less tolerant to stresses during their reproductive than during their vegetative phases of development, so that farmers aim at adjusting growing periods to expose the grain formation to optimal temperatures and to avoid water stress (Minoli et al., 2019).

This work is a major advancement over the previous approaches to phenology adaptation under climate change. (1) Instead of deducing model-specific cultivar parameters, based on statistical relationships built between climate and crop phenology (e.g. van Bussel et al. (2015)), it computes the anticipated end of growing periods (harvest dates) from a farmer's perspective, intending to select the best growing period of a climatic year. Model-specific parameters can then be chosen to represent suitable cultivars to be grown within that growing period. (2) It provides a more sophisticated base for gap-filling of global-scale datasets on growing periods, allowing to parametrize crop phenology in regions where observational data are missing. These include areas outside the current cropland, which is of particular interest for e.g. land-use change studies. In order to assess the potential of cropland expansion or change in crop-type distribution, it is necessary to make assumptions on which agronomic management would be applied to crops grown in new areas, including the selection of locally-adapted growing periods. (3) Finally, it explicitly and dynamically simulates how farmers would adjust both sowing and cultivars under future climate, allowing for dynamically simulating adjustments in farmers' management decisions on sowing and cultivars.

5.1.3 What are the effects of decision-based adaptation in growing periods on crop yields and production under climate change?

Chapter 4 explores crop yield impacts and adaptation under end-of-the-century climate scenarios including CO_2, temperature and precipitation changes. The decision-based approach presented in Chapter 3 is used here to estimate crop sowing and harvest dates adapted to both historical and future climate and to parametrize crop phenology in the global crop model LPJmL.

In the *unchanged management* scenario, farmers are assumed to apply the same sowing dates and cultivars both in the reference time period and at the end of the century, as it is typically done in impact assessment studies (Rosenzweig et al., 2014; Nelson et al., 2013; Deryng et al., 2016). Even with this unrealistic assumption, simulated climate change effects on total calorie production are found to be positive (+9%). At first sight, this result appears in contrast with what has been found in Chapter 2 (drastic production decline with temperature increase). However, it should be noted that the climate scenarios tested here consider also changes in CO_2 and precipitation, which were not included in the previous study. Under counterfactual scenarios with CO_2 concentration fixed at the reference level, climate change impacts are found to be negative for all crops and world regions, indicating that the positive yield response is largely due to the CO_2 fertilization effect that can be realized by C_3 crops.

In the *complete adaptation* scenario, farmers are assumed to adapt sowing dates and cultivars to future climate. In the temperate zones adapted sowing dates occur earlier compared to the reference scenario, as a consequence of an advanced onset of warm temperatures. In contrast, the start of the wet season in the sub-tropics appears to be relatively stable, leading to little variation in sowing dates. The algorithm selects growing periods so as to expose the grain formation to optimal climatic conditions. Adaptation therefore results in shorter, equal or longer growing periods compared to the reference ones. However, due to an overall increase in growing season temperatures, cultivars adapted to future climate are generally of longer maturity classes (except for winter wheat).

This study highlights that accounting for crop phenological adaptation substantially affects estimates of climate change impacts on global crop production under future climate. The decision-based adapted growing periods are shown to generally have positive effects on crop production and yields. On top of the CO_2 fertilization effect, adaptation leverages global calorie production by an additional 10%. The counterfactual scenario with static CO_2 concentration highlights the importance of adapting growing periods, especially in those regions, like the tropics, where CO_2 fertilization is unable to compensate for production losses. However, in certain regions climate impacts cannot be avoided by adjusting crop phenology. Particularly, these are found in areas where the climate conditions become too hot and/or too dry, so that the algorithm cannot find a suitable growing period for crop growth. This might indicate that other adaptation strategies will be needed, possibly including changes in cropping systems (Vermeulen et al., 2018).

5.2 Discussion

5.2.1 Modelling farmers decisions for autonomous adaptation

Farmers modify their agricultural practices to maintain or increase productivity and profitability of their cropping systems and to respond to changing conditions. If scientific knowledge and technology are reliable and readily applicable, farmers and practitioners can benefit from it to improve and adapt their production systems. On the contrary, when science cannot provide adequate advise, they have to look for solutions based on their own experience and trialing (Doré et al., 2011). In short, informed either by science or autonomously, farmers will react to climate change. Therefore, to ignore adaptation in crop models means neglecting a fundamental part of cropping systems' flexibility.

Yet, adaptation of cropping systems to climate change is currently an on-going and unresolved research topic. Due to knowledge gaps on how farmers make decisions, crop modelling is bound to simulate future crop-yield responses under the assumption that farmers will be using the same agricultural practices of today. Alternatively, modelling can inspect sets of possible scenarios to identify the most viable one (Zimmermann et al., 2017; Ruiz-Ramos et al., 2018). Especially if applied at the global scale, this second approach requires substantial computational resources, due to the rapidly increasing number of required scenarios, the more adaptation strategies need to be simultaneously examined (refer to Chapter 2 as an example).

Focusing on crop phenology, this thesis covers fundamental aspects of climate change adaptation. Certainly, the choice of cultivars and sowing dates are agronomic decisions that all farmers make in order to optimize production of grain yield on their farm. In Chapter 3, it is shown how strongly these decisions depend on climate and how current crop phenological patters reflect climatic patterns of different locations. The decision-based algorithm can reproduce current crop phenological patterns (adapted to recent climate) with good approximation and is, more importantly, an effective tool for projecting growing periods under future climate scenarios. This work improves the understanding of the farmers' decision-making process (Chapter 3) and it allows better assessments of future climate change impacts (Chapter 4).

Still, many aspects of agronomic decision making are not accounted for. These include (i) the soil conditions, which determine the actual workability and crop germination; (ii) the year-to-year variation in actual sowing within a given sowing window; and (iii) the spatial variability within the model simulation units (grid cells), because of weather fluctuations or labor organization within individual farms. Furthermore, only mono-cropping systems (growing a single crop per year) have been modelled in this study. Although, these are the most common systems globally (Siebert, Portmann, and Döll, 2010), global warming is changing the growing season length, increasing the area where multi-cropping systems could potentially be implemented (Mueller et al., 2015). Understanding growing period decisions in these systems will require further research.

The results presented in Chapter 4 are of interest for evaluating not only the adaptation potential to future climate, but also the actual capacity of doing so of current production systems. Results show for example that to continue growing the same crops on their current cultivation area, farmers will need to use longer maturing cultivars in most regions. In some cases however, the adapted cropping period may be obtained only if using new cultivars with heat-sum requirements that are currently very marginal or not available at all. The breeding and cultivar release process is long and costly and it would profit from information of breeding targets for climate change adaptation (Challinor et al., 2016). If uncertainty is accounted for, this approach could be of help to breeders. This could complement previously published methods to find analogue agro-climatic conditions in other regions of the globe where the future target germplasm could be already available (Pugh et al., 2016), by providing such indications also where no analogues are found. Moreover, it could allow for identifying trait-selection priorities, based on the identification of growing season limiting factors (e.g. harvest rule and harvest reason, as explained in Chapter 3 and 4).

5.2.2 Agronomic adaptation of crop yields to climate change: looking beyond phenology management

Phenology is not the only agronomic way for adapting crops to a changing climate. Nonetheless, the timing of many other field operations relevant for adaptation is usually defined based on weather and crop phenology (Debaeke and Aboudrare, 2004; Hutchings et al., 2012). For example, most soil-tillage operations need to be carried out outside the crop growing periods, whereas others are possible only at specific phenological stages, such as inter-row cultivation. Fertilizer-use efficiency can be increased if application rates are split to follow the crop nutrient demand throughout its growth pattern. Finally, agrochemical products for pest and disease management need to be applied at specific growth stages to be effective. Therefore, the approach presented in this thesis for dynamically simulating crop phenology adaptation can be the base for implementing these practices within process-based models.

In addition, breeding new cultivars for climate adaptation does not merely target adjustments in phenology, but it may also aim to improve crops' stress tolerance and resistance (Semenov et al., 2014; Mega et al., 2019). This was not taken into account in the studies presented here. However, the rule-based approach for adjusting growing periods to climate relies on biophysically meaningful parameters, such as the range of optimum temperatures for crop development and growth, or the crop sensitivities to water scarcity based on supply and demand of water. This would allow for testing adaptation through cultivars improved for other traits than phenology. For example varying the P/PET ratios or the crop optimum temperature parameters could be used to simulate cultivars with higher or lower tolerance to dry periods or high temperatures, respectively. Also the length of phenological phases is an explicit parameter in the algorithm that can be adjusted to simulate breeding for e.g. longer grain filling. Additionally, the approach could be used for testing the existence of trade-offs between cultivar traits, such as whether enhanced stress resistance comes in compromise with e.g. a worse crop harvest index.

An outcome of this work is that tropical regions are the most threatened by climate change. In the tropics, also when considering CO_2 fertilization effects, stronger climate change impacts were found. Moreover, phenology management does not show a large potential for adaptation there, although it can in many cases partially compensate production losses. The studies in Chapter 2 and 4 both considered that new technology needed for adaptation (i.e. cultivars with adapted phenology) would be equally available across locations. However, research, technology and infrastructures are not equally well distributed. In some regions, adaptation will likely have higher costs to be implemented than in others, e.g. because of the difficult access to germplasm and/or to credit by the local seed producing companies (Langyintuo et al., 2008). This emphasizes the need for research to pay more attention to the location-specific context and preconditions of successful adaptation measures. In fact, if costs are too high it might be more convenient to import food from other regions or to switch cultivation to a different crop, than to invest money in adaptation through technological change or improved cultivars (Stevanović et al., 2016). Such evaluation goes beyond the scope of this thesis and can be better addressed by economics and land use modelling. These disciplines usually rely on biophysical crop yield simulations (Nelson et al., 2013), and will be better informed by biophysical crop-models that simulate yields taking into account cultivar adaptation. Solutions should be assessed not only in view of their feasibility and agronomic success, but also paying attention to their sustainability, as these might come with large-scale transformations (e.g. transition from subsistence to large-scale farming) (Kates, Travis, and Wilbanks, 2012). Along with improving productivity, agronomic practices should particularly preserve natural resources and minimize detrimental effects on the environment. Moreover, they should be accessible and socially fair for farmers (Pretty, 2007). More generally, modelling future development of agriculture and farmers' decision making is an interdisciplinary task that requires the integration of biophysical (e.g. this thesis) and socio-economic perspectives (Popp et al., 2017).

5.2.3 Adaptation will not occur independently of intensification and technological change

The global population is expected to continue rising. Population might increase by 53% until 2100, even in scenarios assuming faster decline in fertility (number of children per woman) (United Nations, 2015b). Together with higher annual per capita income, this is driving up global demand of agricultural products (Godfray et al., 2010; Tilman et al., 2011; Bodirsky et al., 2015; Food and Agriculture Organization, 2018). Because land is becoming scarcer at the same time, an increase in productivity on current cropland is considered essential (Godfray et al., 2010; Tilman et al., 2011; Food and Agriculture Organization, 2018), although shifts towards more sustainable and plant-based diets could reduce this pressure (Willett et al., 2019). Increasing production without expanding agricultural land implies obtaining higher harvest from the same land through intensification, technological progress or other transformative changes in production systems. Moreover, these measures could help compensating some of the production losses due to climate change in those areas where incremental adaptation is not fully effective (e.g. results on irrigation effects in Chapter 2), as long as climate change does not simultaneously diminish the resources (e.g. water supply) needed for such production increase (Elliott et al., 2014).

5.2.3.1 Intensification can be achieved by either increasing cropping intensity or the yield of individual crop cycles

Higher cropping intensity (number of harvests per year) is not always a practicable option. As shown in Chapter 3 growing periods have severe constraints due to temperature and precipitation seasonality, which often limit even a single crop cycle per year. However, in tropical regions and in some warmer temperate zones, multi-cropping systems are already a common practice (Siebert, Portmann, and Döll, 2010; Waha et al., 2013; Kollas et al., 2015; Mathison et al., 2018). Further warming can potentially allow for higher cropping intensity and can increase the area where multiple harvests per year are possible (Mueller et al., 2015). This will be possible only through the selection of appropriate crop and cultivars sequences with compatible phenological cycles. The modelling approach presented in Chapter 3 could only partially allow for the assessment of such systems. For example, it can be further extended to include agronomic decisions on multi-cropping sequences, by prescribing a second sowing after the main crop cycle and letting the algorithm seek for possible secondary harvest dates. Similarly, for simulating crop rotations, additional rules should be defined, to avoid overlapping growing periods of two crop cycles.

Field crops are rarely exposed to optimal conditions throughout the entire growing season. Limitations are caused by climate, soil conditions and imperfect management. Improving management in such a way as to minimize limiting factors for crop growth is what all farmers try to do, although it has been observed that many cropping systems throughout the world stay below potentially achievable yields (Lobell, Cassman, and Field, 2009). The yield potential is the theoretical upper limit of yield at a given location. It is the yield of a crop grown without any biophysical limitations other than uncontrollable factors, which for field crops are essentially the climate and the soil properties. Yield gaps (differences between potential and actual yields) are largely caused by deficiencies in soil water and macronutrients (nitrogen, phosphate and potash) (Licker et al., 2010; Mueller et al., 2012). Hence, intensification can be achieved in many regions by increasing agronomic inputs to reduce crop stresses. In fact though, reaching 100% of the yield potential is generally not economically viable, because farmers aim at maximizing profit and not yields. For this reason, in most irrigated systems, major grain crops reach at maximum 80% of their yield potential (Lobell, Cassman, and Field, 2009). It should be noted that the yield potential is a hypothetical metric that requires assumptions on a locally optimized combination of sowing date and cultivar maturity (Lobell, Cassman, and Field, 2009; Fischer, 2015). Therefore, in order to estimate future yield potentials and gaps it is once more necessary to project how sowing dates and cultivar selection will be adapted in response to changes in climate and technology.

5.2.3.2 Technological change in agriculture aims at improving crop yields at both the biological (plant processes) and management (plant growing conditions) levels

Breeding programs and bio-technologies have allowed extraordinary increases in actual and potential crop yields (Fischer, 2015). Current cultivars are substantially different from e.g. those antecedent the Green Revolution, and future plants will be different from today's ones. Traits such as phenology, canopy structure, or harvest index have been strongly modified in the past (Khush, 2001). The progress is not always continuous, but can have abrupt increases, as during the Green Revolution, or can reach plateaus as observed in major cereal-producing regions in the past two to three decades (Ray et al., 2012; Grassini, Eskridge, and Cassman, 2013; Food and Agriculture Organization, 2018). Future breeding trends are difficult to project. Nonetheless, breeding for stress tolerance (e.g. heat or water) can be expected to be strategic for enhancing yields, even in a world without climate change, as this would allow crops to exploit conditions outside their current physiological limits (Lobell, 2014).

Technological change has been greatly transforming also management practices in agriculture through mechanization and agro-chemistry (Khush, 2001). Currently, the increasing access to data and information along with new technologies (e.g. remote-sensing), are providing farmers with tools that can improve yields and optimize the use of agronomic inputs, also accounting for within-field variability (e.g. precision farming) (Godwin et al., 2003; Zarco-Tejada, Hubbard, and Loudjani, 2014). Moreover, the increasing reliability of weather forecasts and early warning systems allows for better planning of operations, such as scheduling of irrigation and fertilization, or prediction of disease outbreaks (Calanca, 2014; Olatinwo and Hoogenboom, 2014).

Crop models are very seldom able to represent yield trends in time due to bio-technological change, as this would imply a dynamic change in crop traits. Exceptions are the approaches by Glotter and Elliott (2016) and Elliott et al. (2018), in which parametrization of crops and cultivars (thermal-unit requirements of vegetative and reproductive phases, kernel number, radiation use efficiency) is changed linearly along the simulation time series to represent genetic yield advancement.

It is to some extent easier to represent trends in management (e.g. extension of irrigation facilities, increase in fertilizer application or use efficiency, change in sowing date), due to better data availability (Kucharik, 2006; Conant, Berdanier, and Grace, 2013; Siebert et al., 2015; Lawrence et al., 2016). Economic models can instead include (exogenous or endogenous) trends in crop productivity, but typically do so at an aggregated level, therefore without distinguishing the kind of technology that produces the change (Dietrich et al., 2014). From a modelling perspective, it is therefore interesting to have a better understanding of potentials for productivity increase, at both the process and aggregated scales. The evaluation of benefits from closing the yield gap or of investing in breeding programs and technological change should be considered under the additional constraint of climate change, as this affects the crop yield potential. Profitable yield increases under today's conditions can result to be ineffective in the future, if e.g. the same crops will not be able to adapt to new climate.

5.3 Outlook

5.3.1 Applications of the adaptation modelling approach

This thesis has shown that the impacts of climate change on crop yields and production can be greatly modified by the adaptation of crop phenology to different environmental conditions. This aspect has not yet been considered, or at least not consistently and systematically analyzed, in most previous global-scale analyses (Rosenzweig et al., 2014; Frieler et al., 2017a). The approach presented here to estimate both sowing and harvest dates is ready for application in future agricultural climate impact assessments. An interesting feature is that the algorithm is driven by only climate data and crop-specific parameters, making it crop-model independent and very flexible for a number of applications. Since this approach has been developed for being combined or directly implemented in GGCMs, this is its first area of application (Chapter 4). Moreover, the simulated sowing and harvest dates can be used in statistical models to aggregate weather or climate statistics within adapted growing periods (e.g. Dillon, McGee, and Oseni (2015) and Lobell and Burke (2010)).

With GGCMs being central components of biophysical Earth System Models (McDermid, Mearns, and Ruane, 2017) as well as of Integrated Assessment Models (van Vuuren et al., 2009), the inclusion of cultivar adaptation algorithms will allow for simulating more realistic trajectories of food production and climate change impacts on agriculture with these modelling frameworks. Moreover, it will be possible to assess how robust the results are that have been obtained to date without consideration of cultivar selection and changes in growing periods.

5.3.2 Further improvements and model development

GGCMs need to better represent phenological phases, as often these models (e.g. LPJmL (Schaphoff et al., 2018), GEPIC (Liu et al., 2007), PEPIC (Liu et al., 2016c)) do not simulate other intermediate phenological stages than sowing and maturity. Phenological phases, especially those related to yield formation (e.g. flowering, grain set and grain filling), are also of special importance in the context of climate change and adaptation (Barber et al., 2015). The approach presented in Chapter 3 has considered the central role of the crop reproductive phase. Due to the lack of data on additional within growing period information (e.g. anthesis dates) at the global scale, this aspect could not be validated. However, this will be necessary especially for simulating heat-stress events around flowering, which are recognized as one of the main mechanism of how global warming affects crop productivity (Hatfield et al., 2011a). In addition, the approach in Chapter 3 includes uncertainty about the time between maturity and harvest. After maturity it is common to let the grains dry before harvest and storage. This management operation further exposes the crop to microbes and animals that can damage grain quality and produce further losses (Kaaya et al., 2005). The maturity-to-harvest phase is often neglected or assumed constant in crop models, but in fact it is driven by weather variables and, in principle, it can also be modeled. This may be particularly relevant in view of recently developed modelling approaches that simulate the effects of pests and diseases on crop yields, also at the global scale (Deutsch et al., 2018).

In this thesis, data on sowing and harvest dates have been used for parametrizing the existing phenological modules as-they-are in the GGCMs. Nonetheless, along with improving crop models by better representing agronomic management, it is crucial to keep them up-to-date with the most recent findings on crop pysiological responses to climatic factors (Rötter et al., 2011). Generally, in process-based crop models the responses of phenological development rate to temperature are based on the thermal-time concept. The different thermal-time functions implemented in crop models have been shown to be a large source of uncertainty for simulating both crop phenology and growth, especially at supra-optimal temperature levels (Wang et al., 2017). Recent experimental findings have demonstrated that the temperature-driven rates of many processes, including phenology, follow a common response function (Parent and Tardieu, 2012). Improving crop phenology representation in models should consider including these new finding (e.g. substituting old temperature response functions with more sophisticated approaches that better reflect the understanding of phenological development), in order to reduce uncertainty in the modelled speed of crop progress towards maturation and year-to-year variability of harvest dates. Furthermore, the type of rate's response functions to temperature apparently is conserved across species and has not been affected by breeding efforts so far, making it unlikely to be affected by breeding in the future (Parent and Tardieu, 2012).

The central chapter of this thesis presents a rule-based model that can dynamically simulate farmers' decisions for adjusting cropping periods under changing climate. The approach has been validated against two global scale observation-based datasets (MIRCA2000 and SAGE). The limits of the two datasets are the relatively low resolution in space and the absence of temporal resolution, as they provide only one point in time (around the year 2000). Future development of this approach will profit from datasets with higher resolution. Particularly, the time dimension would be necessary for investigating the year-to-year variability of phenology as well as impacts of climate change on cropping periods and adaptation over time. Remote-sensing data with very high spatial and/or temporal resolutions that separate different crop types are becoming available (Vreugdenhil et al., 2018) and can be used for improving understanding and modelling of farmers' decision making, as well as for inferring agro-technological trends from the observed phenology (e.g. increasing duration of grain filling phase in US maize (Glotter and Elliott, 2016)). Along with these top-down approaches, modelling would profit from accessing information on breeding programs and their strategies for selecting cultivars for phenological and other traits (e.g. water stress tolerance).

Finally, this thesis has addressed phenological adaptation of grain crops only. Other crop types, such as pulses (bean, peas), root crops (potato, cassava) and oil crops (sunflower, rapeseed) will be relevant for future global food production and their adaptation will need to be assessed. This will require additional research to gain understanding on how farmers select cultivars and growing periods for these crops.

A
Supplementary Information for Chapter 2

Global response patterns of major rainfed crops to adaptation by maintaining current growing periods and irrigation

1 Supporting information

1.1 GGCMI phase 2 CTWN-A protocol

The overall scientific rationale of the GGCMI phase 2 protocol (`https://agmip.org/protocolsandreports/`) is to conduct a comparative analysis of the strategies and mechanisms used in different models to describe Carbon, Temperature, Water, Nitrogen and Adaptation (CTWN-A) processes, interactions, and feedbacks. This analysis framework builds on the AgMIP Coordinated Climate-Crop Modeling Project (Ruane et al., 2013; McDermid et al., 2015) efforts to compare models, sites, and uncertainty, and extends the concept now to global gridded simulations. This also provides a basis for comparison between grids and site-based networks. Moreover, it aims at enhanced understanding of how models work, characterizing models by sensitivity to drivers, and assesses aggregated model responses at different aggregation levels (e.g. Köppen-Geiger climate zones).

GGCMI participants run models globally using harmonized input data. The AgMERRA climate data set from 1980-2010 is used as in phase 1 (Elliott et al., 2015). Groups that require data on long-wave radiation are asked to use the data from the Princeton GF (version 1, not PGFv2). Nitrogen and CO_2 are specified at globally uniform levels and are not provided as spatially explicit data sets. Nitrogen fertilizer is to be applied in 2 doses, 50% at planting and 50% at a crop- and pixel specific date (40 days after planting for all spring crops, case-specific for winter wheat). All other sources of nitrogen supply (mineralization, fixation by soy) have to be reported in the outputs, no deposition or soil-only fixation should be applied. Modelers are asked to find implement themselves scenarios of CTWN offsets.

Four levels of participation are defined (*low, mid, high, super tier*). GGCM crop-specific output variables of highest priority have to be submitted per growing season: yield (t DM ha^{-1} yr^{-1}); total above ground biomass yield (t DM ha^{-1} yr^{-1}); actual planting date (day of year); anthesis date (day of year), maturity date (days from planting); applied irrigation water (mm yr^{-1}), evapotranspiration (growing season sum, mm yr^{-1}).

To reduce the computational burden, regions that are considered unsuitable are cut out of the simulation. Unsuitable areas are defined according to global Agro-ecological Zones (GAEZ, Fischer et al., 2012). There are a few cases, where (at the resolution of 0.5 degrees) according to GAEZ, the pixels is classified as dominantly unsuitable, but the cropland masks (MIRCA2000) assign cropland to these pixels. To ensure that all cropland currently used in the aggregation is also simulated by the groups, only pixels that are predominantly unsuitable ($\geq 90\%$) and do not contain any cropland (according to MIRCA2000) are excluded. By excluding the so defined unsuitable land, simulation results (all crops everywhere) can be aggregated by any land-use pattern in subsequent analyses.

1.2 Model characteristics and protocol implementation details

1.2.1 CARAIB

CARAIB simulates the crop development from sowing to harvest, requiring a certain (crop-specific) heat accumulation to be reached. A cultivar is attributed to each grid cell as a function of the cell growing season temperature and soil water availability (see below). To germinate a crop needs to accumulate some temperature and soil water conditions must also be suitable for seed germination, so that some delay can occur between sowing and germination. For instance, with a base temperature of 0°C, wheat germinates when GDD0 = 140°Cd and only if soil water conditions are suitable. Wheat reaches maturity when GDD0 attains at least 1800°Cd but some cultivars require more (up to 4000°Cd). In the model, stress occurs under critical soil water content and (minimum) temperature. CARAIB considers crop stress on growth processes from cold temperatures below 0, 8, 7, 0, -2 °C for maize, rice, soybean, spring wheat, winter wheat respectively. If temperature is lower than crop tolerance, the crop biomass is impacted but plant is not necessarily killed. In this case, crop can reach maturity but with insignificant yield.

CARAIB follows a modified protocol with harmonized sowing dates, while the model was not calibrated to match observed maturity dates of each grid cell. The simulated growing season of a crop is constrained by observed cropping calendars. Specifically, Sacks et al. (2010) is used to define the crop-specific maximum growing season length. For instance, if wheat does not reach maturity within 200 days, it is not harvested. Minimum and maximum GDD sums (extreme cultivars) are derived from observed growing period lengths, reported for each crop by Sacks et al. (2010). Between these extreme cultivars, there are a series of intermediate cultivars. A cultivar is attributed to each grid cell as a function of the cell temperature over the growing period (temperature accumulation) with soil water availability limiting the growing period length. The new-cultivar adaptation measure was implemented based on the partially-harmonized growing period length obtained under the baseline temperature scenario (T0). Adaptation was based on temperature only, while water limitations were kept constant under the rainfed as well as the irrigated scenarios.

1.2.2 GEPIC

GEPIC simulates the phenological development rate as null below T_{min}, equal to $T_{day} - T_{min}$ between T_{min} and T_{opt}, and maximum at T_{opt}. To harmonize the growing periods growing degree days only were tuned. Default parameters from EPICv0810 for T_{min} and T_{opt} were used. T_{min} and T_{opt} together with long-term (1980-2010) monthly climate data were used to calculate the average GDD in each pixel based on reported harvest and planting dates. GEPIC provided simulation results for a subset of T levels. The output variables of the missing levels (either T1 & T3, or T2) were derived by linear interpolation.

1.2.3 LPJ-GUESS

LPJ-GUESS simulates the phenological development rate as null below T_{min} and above T_{max}, and maximum at T_{opt}. To harmonize the growing period GDD to maturity only were tuned. The GDD sum to maturity was calculated automatically in the no-adaptation T0 simulation based on a 10-year running mean of GDD sum over a default growing period (Lindeskog et al., 2013). The resulting annual GDD sums over 1980-2010 were read in as external forcing for all no-adaptation simulations under perturbed temperature. Simulations with growing period adaptation adjusted GDD sum to maturity based on the above running mean method throughout the simulation. LPJ-GUESS provided simulation results for a subset of crops: maize, spring wheat, winter wheat.

1.2.4 LPJmL

LPJmL simulates the phenological development rate as null below T_{min}, otherwise it is $T_{day} - T_{min}$. To harmonize the growing periods GDD only were tuned. Simulations with increased GDD requirements were conducted, so that crops would grow beyond the prescribed harvest day and recorded the GDD accumulated on that day. For the CTWN-A simulations, the recorded GDD on the harvest day was averaged over the AgMERRA time period and prescribed per pixel and crop. Prescribed sowing dates are exactly met, prescribed maturity dates are met on average. Vernalization in winter wheat made GDD pre-computation more complicated and maturity dates may be less accurate there.

1.2.5 pDSSAT

pDSSAT simulates phenological development rate as null below T_{min} and maximum at T_{opt}. Different T_{opt} values are defined for vegetative and reproductive stages. Phenological phases for maize and rice are defined as time from sowing-to-anthesis and from anthesis-to-maturity. For soy the following phases are defined: EM-FL, Time between plant emergence and flower appearance (R1) (photothermal days); FL-SH, Time between first flower and first pod (R3) (photothermal days) FL-SD, Time between first flower and first seed (R5) (photothermal days) FL-LF, Time between first flower (R1) and end of leaf expansion (photothermal days) SD-PM, Time between first seed (R5) and physiological maturity (R7) (photothermal days). For wheat the following phases are defined: P1, Duration of phase end juvenile to terminal spikelet (PVTU) P2, Duration of phase terminal spikelet to end leaf growth (TU) P2FR1, Duration of phase terminal spikelet to jointing (fr P2) P3, Duration of phase end leaf growth to end spike growth (TU) P4, Duration of phase end spike growth to end grain fill lag (TU) P4FR1, Duration of phase end spike growth to anthesis (fr P4) P4FR2, Duration of phase anthesis start to anthesis end (fr P4) P5, Grain filling (excluding lag) phase duration (°Cd).

1.2.6 PEPIC

PEPIC simulates the phenological development rate as null below T_{min} and maximum at T_{opt} (default values of the EPIC model). To harmonize the growing periods GDD only were tuned. PEPIC provided simulation results for a subset of T levels. The output variables of the missing levels (either T1 & T3, or T2) were derived by linear interpolation.

1.2.7 PROMET

To simulate the crop phenological progress, the applied version of PROMET (v7) uses a curvilinear (bell-shaped) temperature response function of crop development rate. Three parameters (T_{min}, T_{opt}, T_{max}) are used for calibrating the function: the rate is null below T_{min} and above T_{max}, and is maximum at T_{opt}. In addition, vernalization and light effect potentially inhibit phenological progress. Water stress is considered indirectly via the leaf temperature. PROMET uses leaf temperature, which leads to different phenology between rainfed and irrigated crops and all W-dimensions, because reduced water supply results in increased leaf temperatures that usually accelerates phenological development, but could also decrease phenological development rates, if temperature is already beyond the cardinal temperature of T_{opt}. In addition to drought mortality, PROMET considers temperature mortality (due to heat or extreme frost events). Besides phenological development and photosynthesis rates, heat stress impacts on leaf temperature and thus on stomatal conductance and transpiration and thus feed backs to development and photosynthesis. With exception of the phenological impacts, none of these effects are permanent. Leaf color and thus PAR (photosynthetic active radiation) is affected by an increase in brown leaf pigments, but only during senescence. Browning of leaves during short-term heat events in not considered. To harmonize the growing periods, sowing dates were prescribed from the given data set and the model harvest dates were pre-calculated. The offset between simulated harvest dates and given harvest dates were used to calibrate a phenological acceleration/retardation factor. Then the model was run again, this time matching the given dates for sowing and harvest. On some grid cells, the pre-calculation did not succeed, e.g. due to crop failure. In this case, no phenological acceleration/retardation factor could be calculated. These grid cells were masked out and yield is set to NA. PROMET is applied at hourly simulation time step. The 3-hourly ERA-I data is temporally interpoltated to hourly data. PROMET outputs report yield failures as NA.

Table S1: GGCM phenology parametrization. T_{min}, T_{opt}, T_{max} are respectively the minimum, the optimum and the maximum cardinal temperatures of the phenological development response function to temperature. GDD_{min} and GDD_{max} are the minimum and maximum of the growing degree days range used by the GGCMs to calibrate thermal-time requirements. Parameters that are not included in the response function are indicated as NA. Non-reported values are left blank.

GGCM	Param.	maize	rice	soy	spring-wheat	winter-wheat
CARAIB	Tmin	8	8	7	0	0
	Topt	NA	NA	NA	NA	NA
	Tmax	NA	NA	NA	NA	NA
	GDDmin	1000	1000	1500	1800	2000
	GDDmax	3000	4000	3600	4000	4000
GEPIC	Tmin	8	10	10	5	0
	Topt	25	25	25	20	15
	Tmax	NA	NA	NA	NA	NA
	GDDmin	200	200	200	200	200
	GDDmax	4280	3728	3227	5291	6180
LPJ-GUESS	Tmin	8	NA	NA	0 - 8	0 - 8
	Topt	NA	NA	NA	24 - 29	24 - 29
	Tmax	NA	NA	NA	35 - 40	35 - 40
	GDDmin	100	NA	NA	100	100
	GDDmax	5059	NA	NA	5768	5791
LPJmL	Tmin	5	10	10	0	0
	Topt	NA	NA	NA	NA	NA
	Tmax	NA	NA	NA	NA	NA
	GDDmin	700	700	700	700	700
	GDDmax	unlimited	unlimited	unlimited	unlimited	unlimited
pDSSAT	Tmin	8	8			
	Topt					
	Tmax					
	GDDmin					
	GDDmax					
PEPIC	Tmin	8	10	10	5	0
	Topt	25	25	25	20	15
	Tmax	NA	NA	NA	NA	NA
	GDDmin	unlimited	unlimited	unlimited	unlimited	unlimited
	GDDmax	unlimited	unlimited	unlimited	unlimited	unlimited
PROMET	Tmin	8	12-15	15-17	0	0 - 8
	Topt	30	22-28	24-26	25	19-24
	Tmax	42	40	40	37	30-35
	GDDmin	NA	NA	NA	NA	NA
	GDDmax	NA	NA	NA	NA	NA

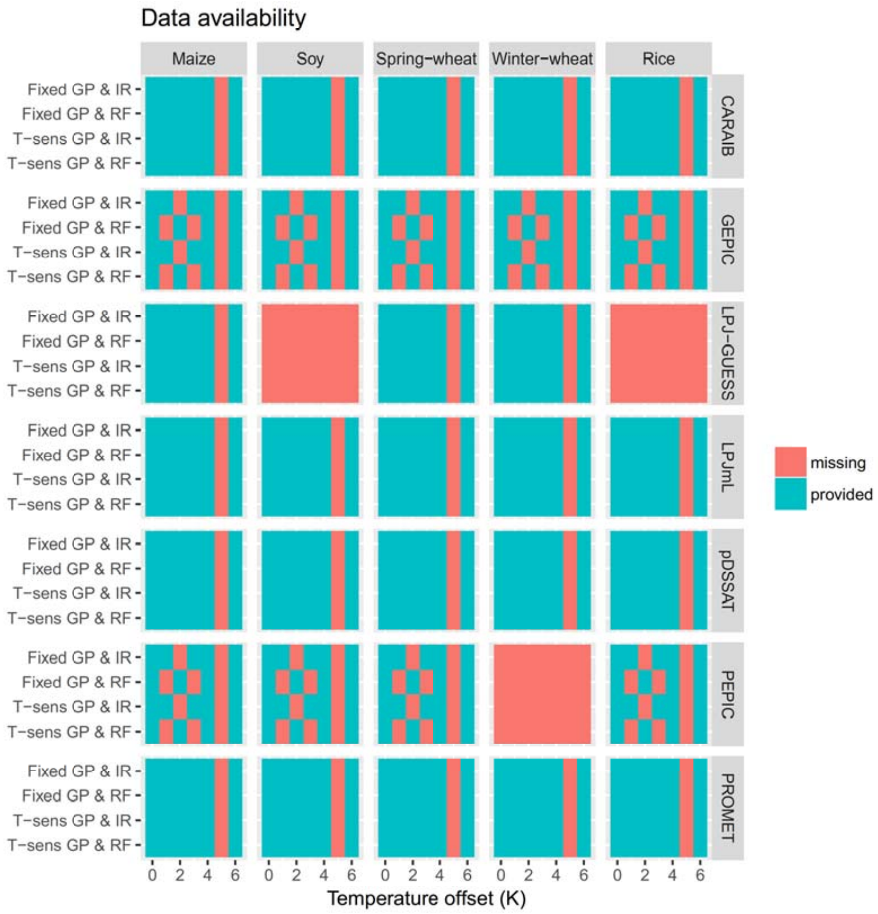


Figure S1: Available crop model simulations for each model, crop, temperature offset and management setting used in this study. Simulation setups missing (except for LPJ-GUESS rice, LPJ-GUESS soy, and PEPIC winter-wheat) are interpolated as described in Section 2.2.2.

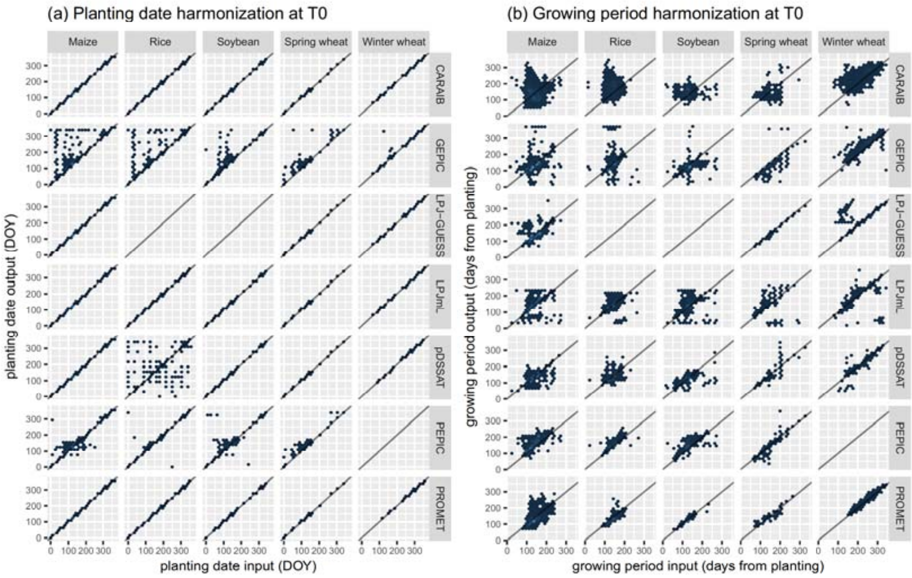


Figure S2: Evaluation of the growing period harmonization across GGCMs (T0, *historical management* setting). Prescribed planting (a) and maturity (b) dates are plotted against realized dated in each model (rows) and for each crop (column). The grey line is the 1:1 line. Across the model ensemble and crops, 94% of the cultivated cells have a modeled planting date within ±3 days compared to the prescribed dates. CARAIB, LPJ-GUESS, LPJmL and PROMET for instance meet these dates in all cells, while others like PEPIC, GEPIC or pDSSAT, have large systematic errors for some of the crops and do not meet these dates in up to 44% of the cells. Across the model ensemble and crops, only 40% of the cultivated cells have a modeled maturity date within ±3 days, and four models (CARAIB, PEPIC, PROMET, LPJmL) out of seven have maturity dates deviations larger than ±14 days from the observed in 22% or more of the cells.

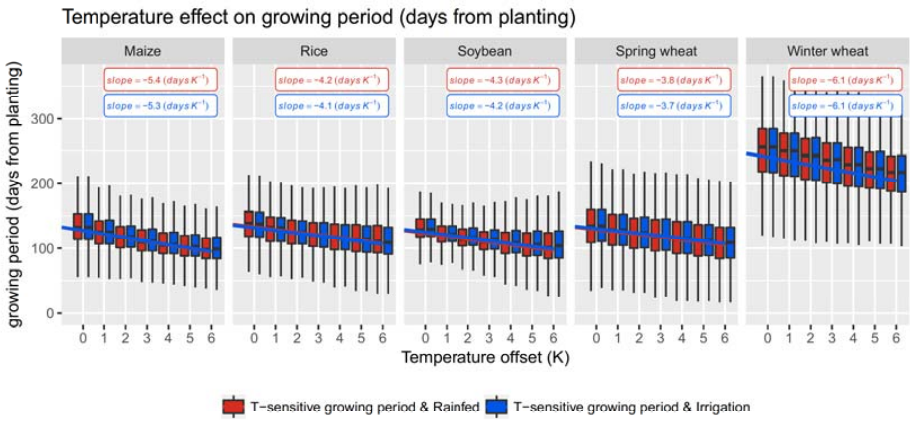


Figure S3: As Figure 2a but for both rainfed and irrigated crops.

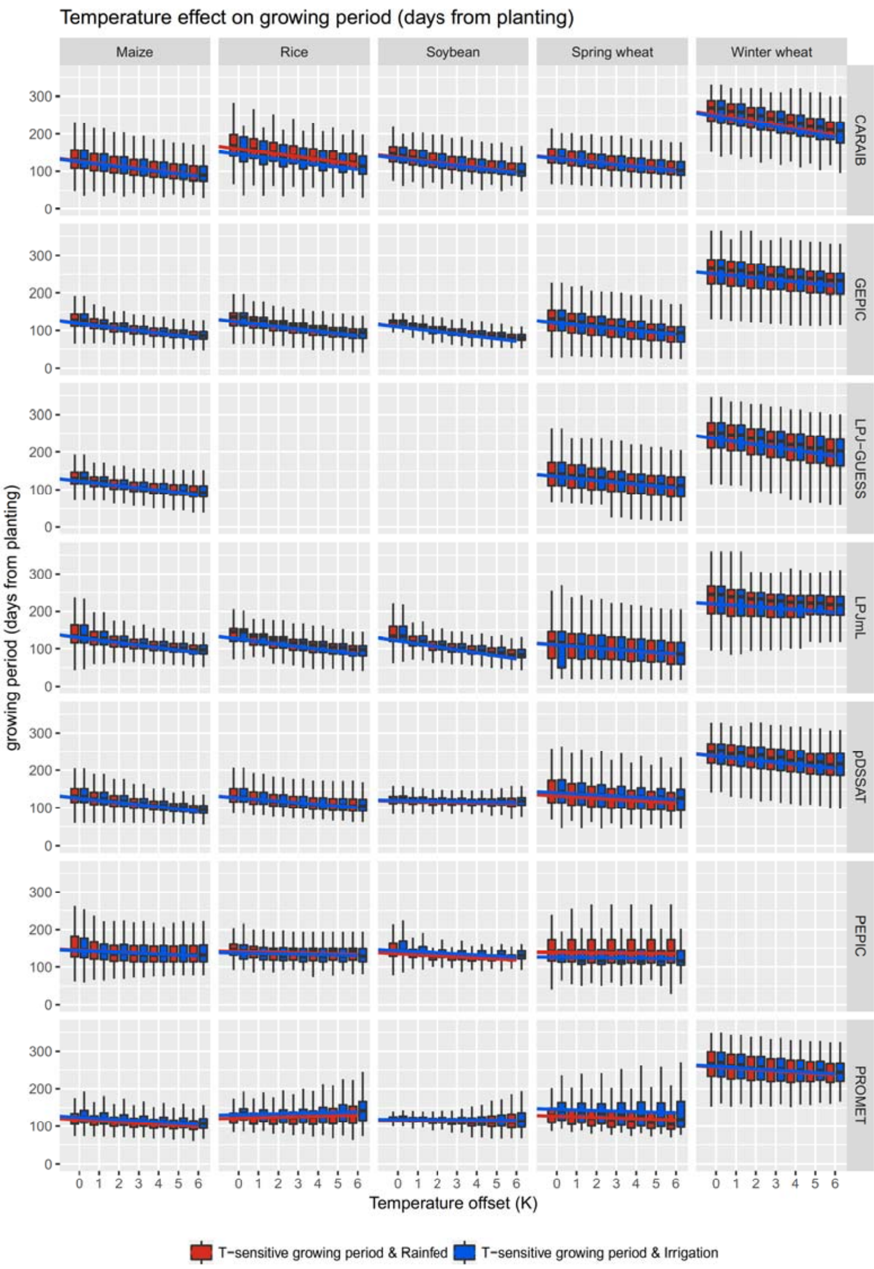


Figure S4: As Figure 2a but for both rainfed and irrigated crops for each GGCM.

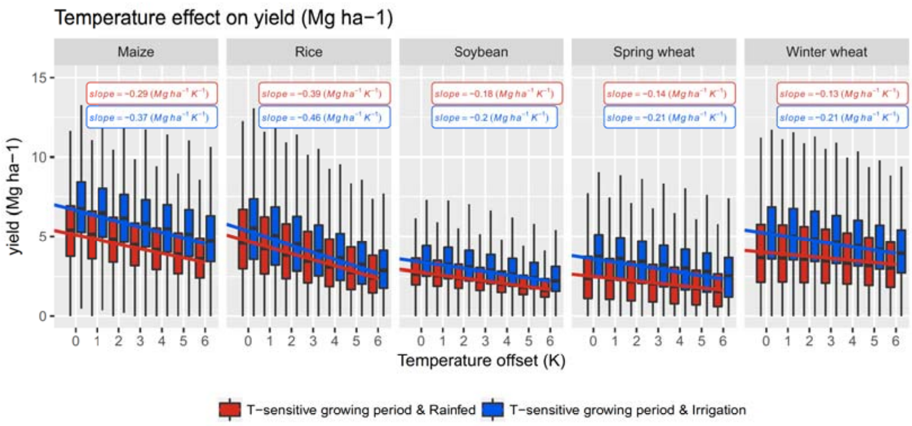


Figure S5: As Figure 2b but for both rainfed and irrigated crops.

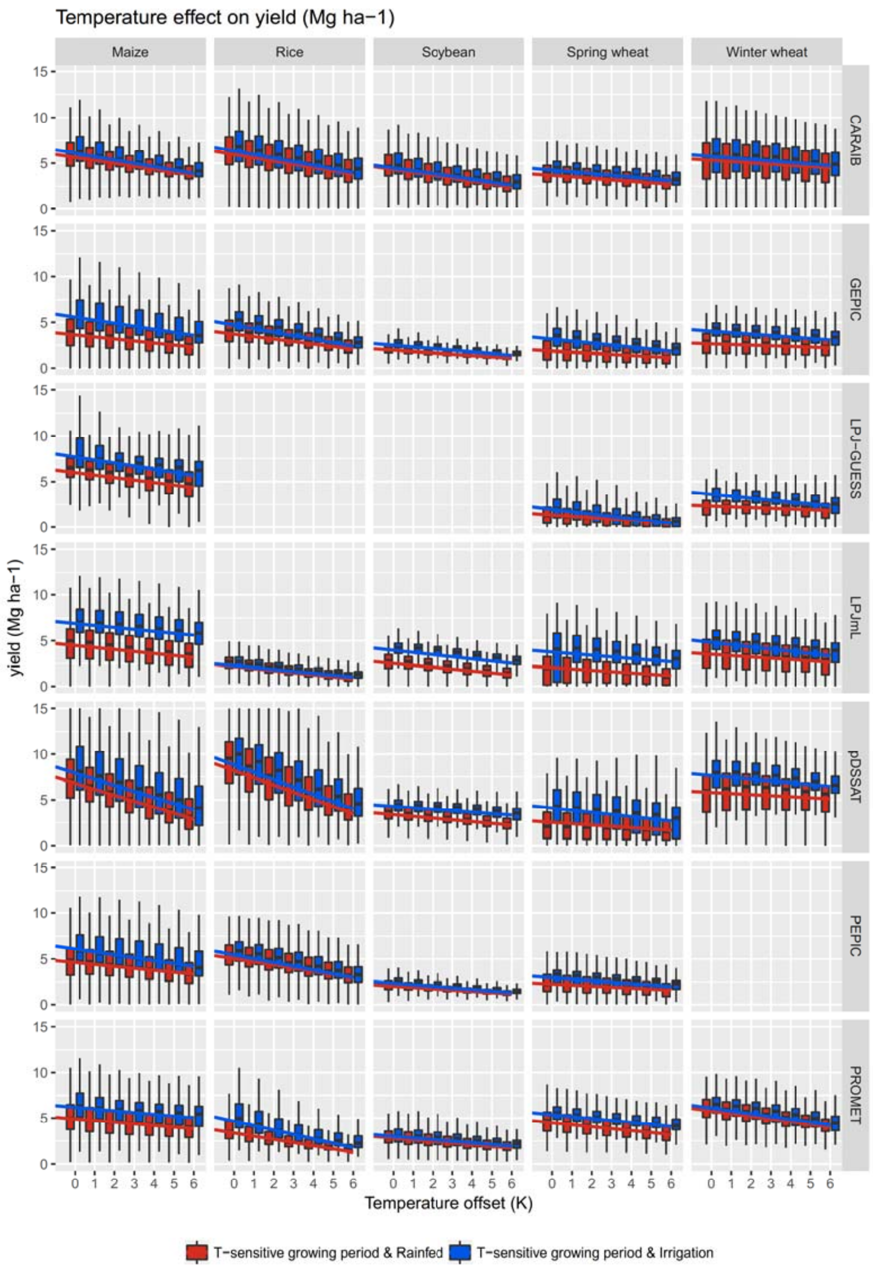


Figure S6: As Figure 2b but for both rainfed and irrigated crops for each GGCM.

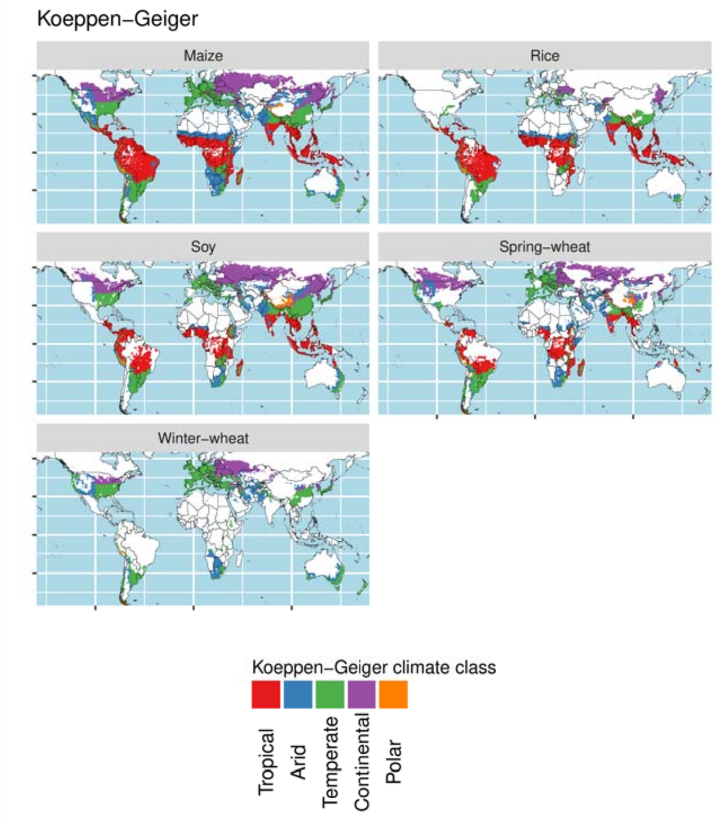


Figure S7: Cropland allocation in specific Koeppen-Geiger climate zones.

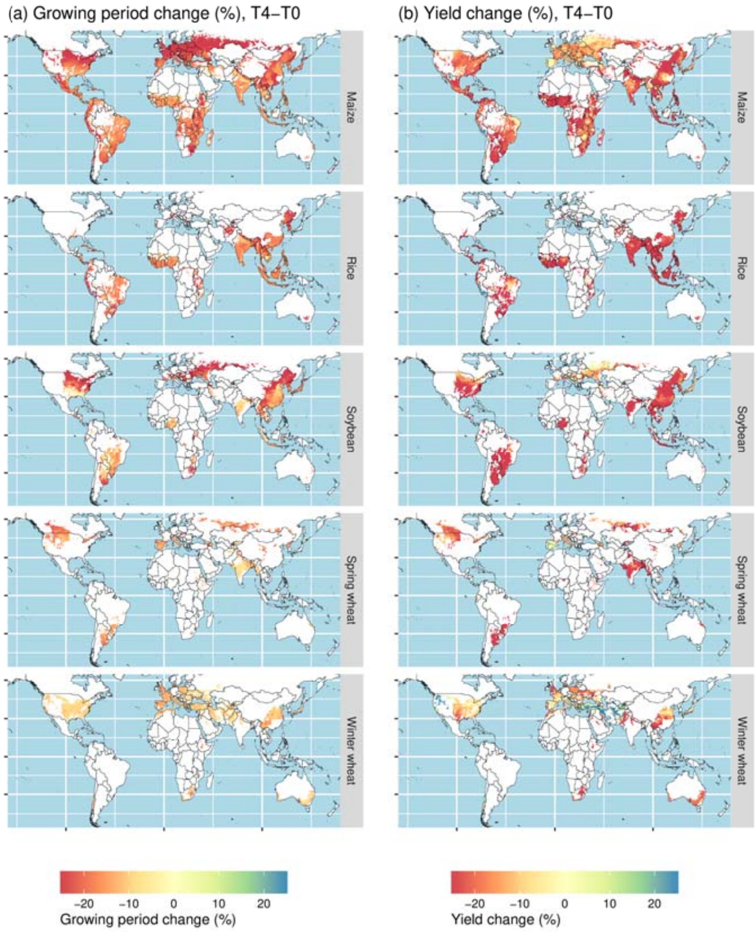


Figure S8: (a) Growing period change (%) and (b) yield change (%) with 4 K temperature increase. Each panel shows crop-specific ensemble median of the difference T4-T0 under static management ($CV_{old} + RF$).

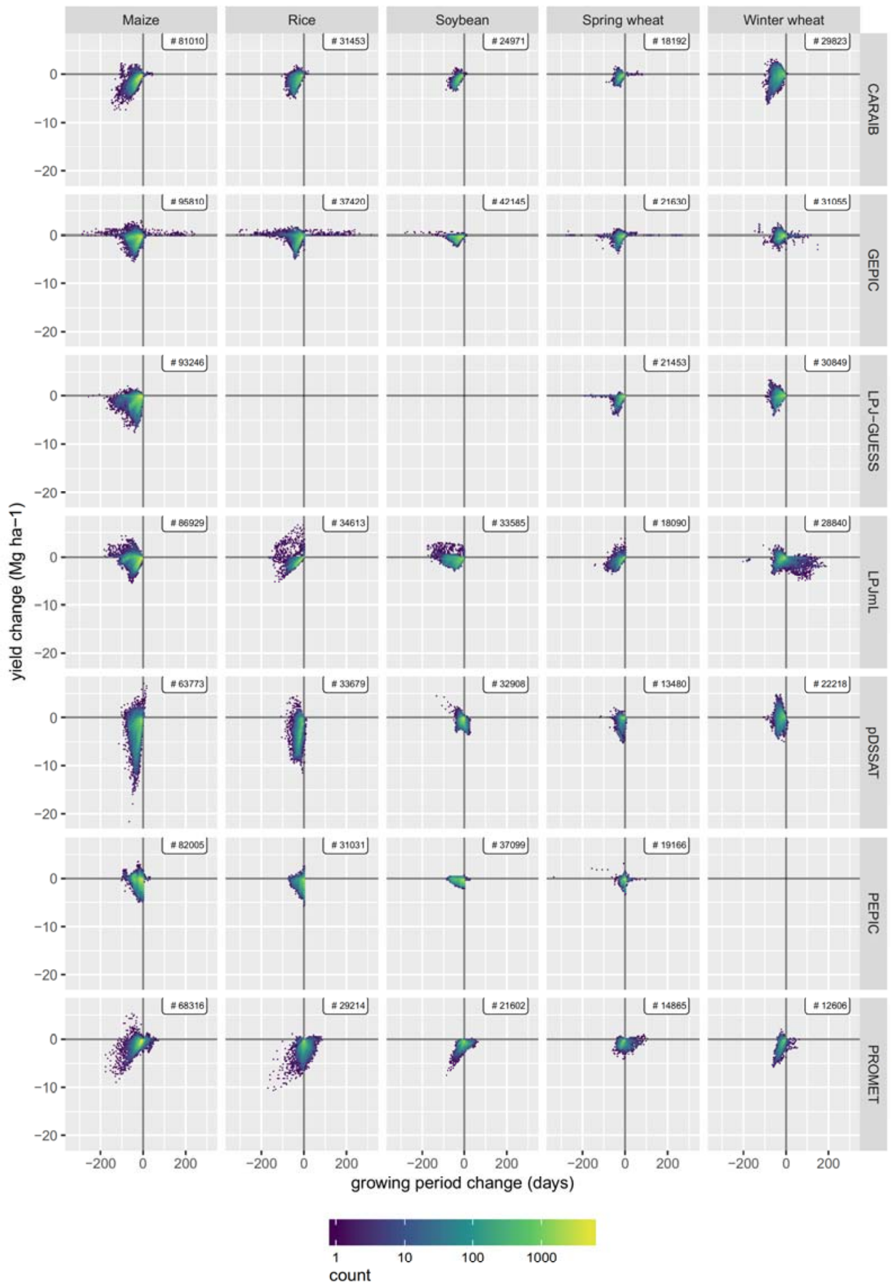


Figure S9: As Figure 2c but for both rainfed and irrigated crops for each GGCM.

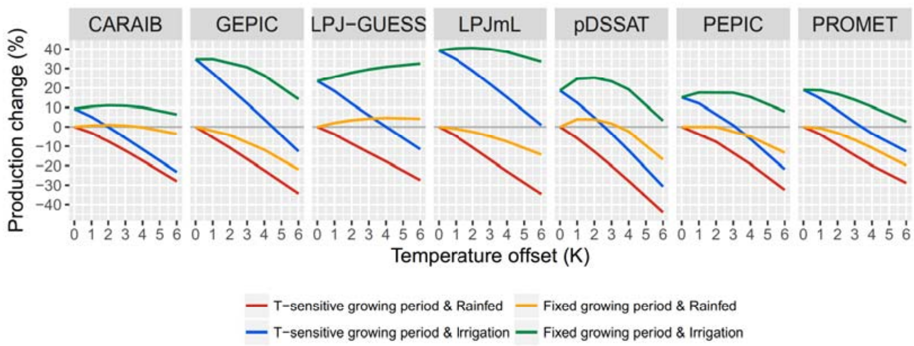


Figure S10: As Figure 3 (All crops), but for each GGCM.

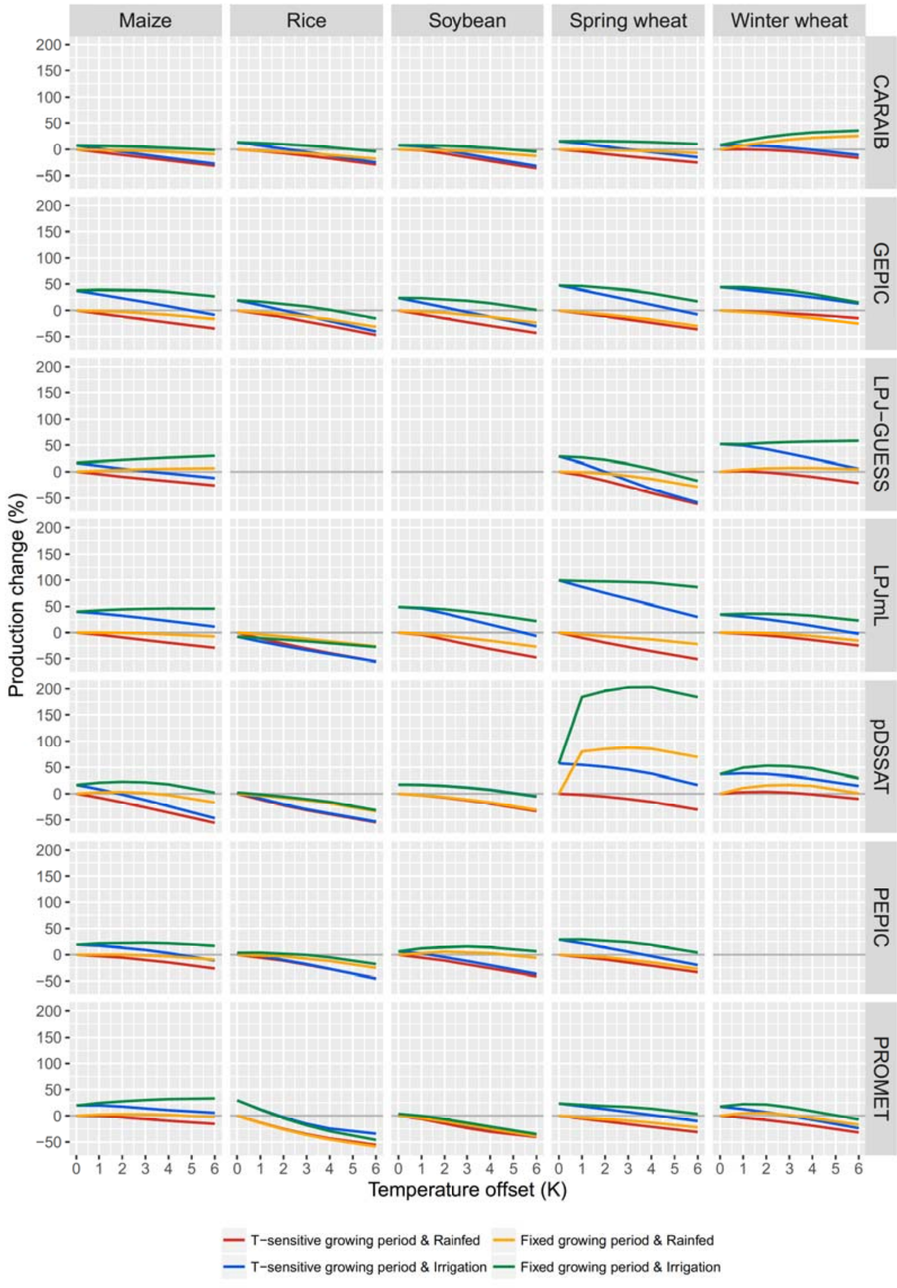


Figure S11: As Figure 3 but for each GGCM.

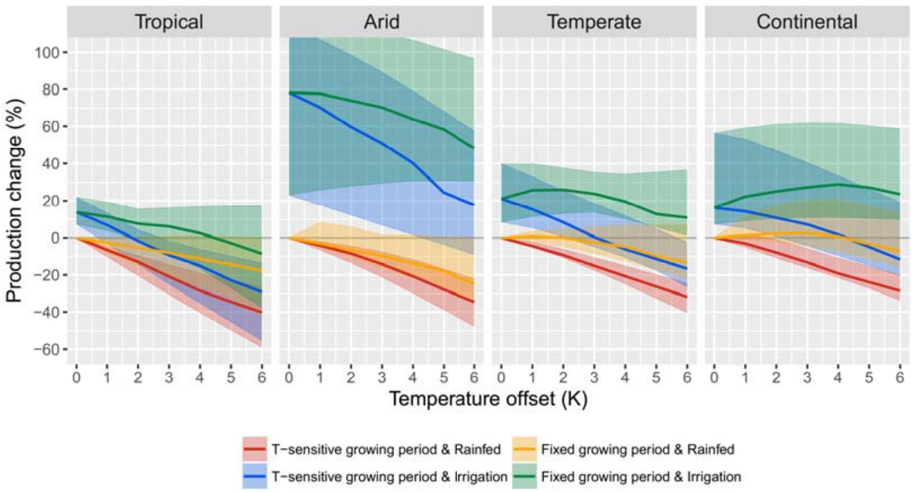


Figure S12: As Figure 3a, but for the Köppen-Geiger climate zones.

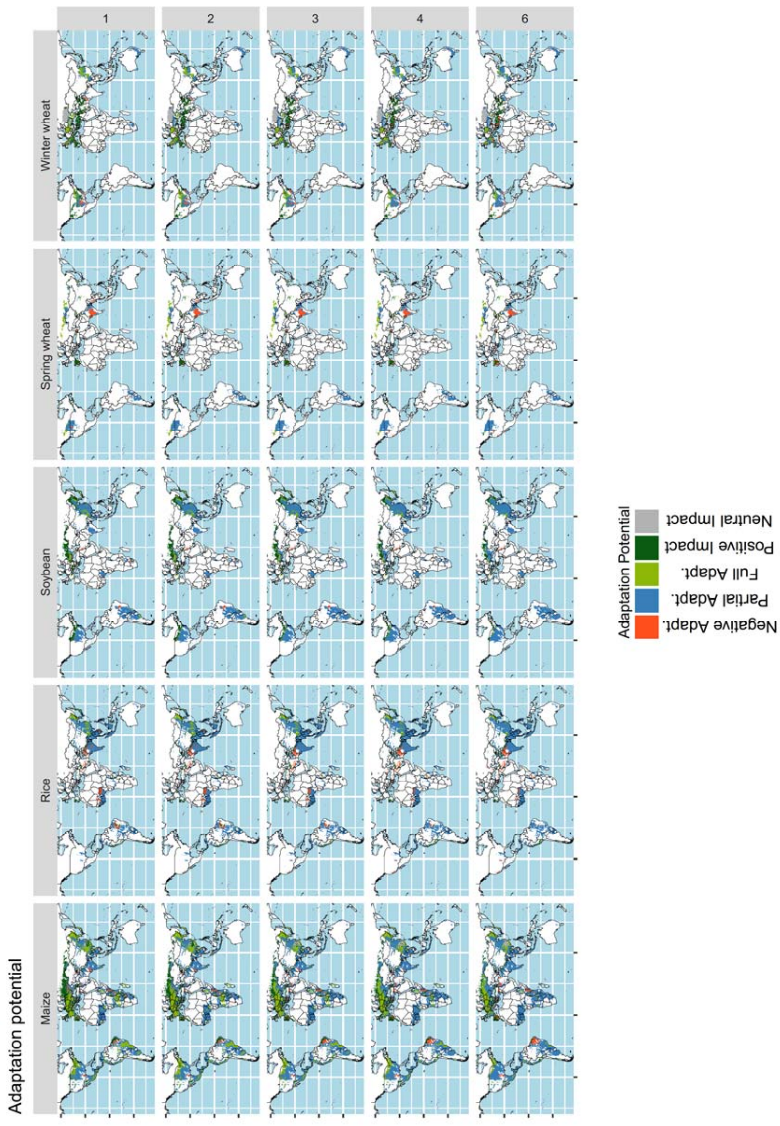


Figure S13: As Figure 4a, but for each temperature offset.

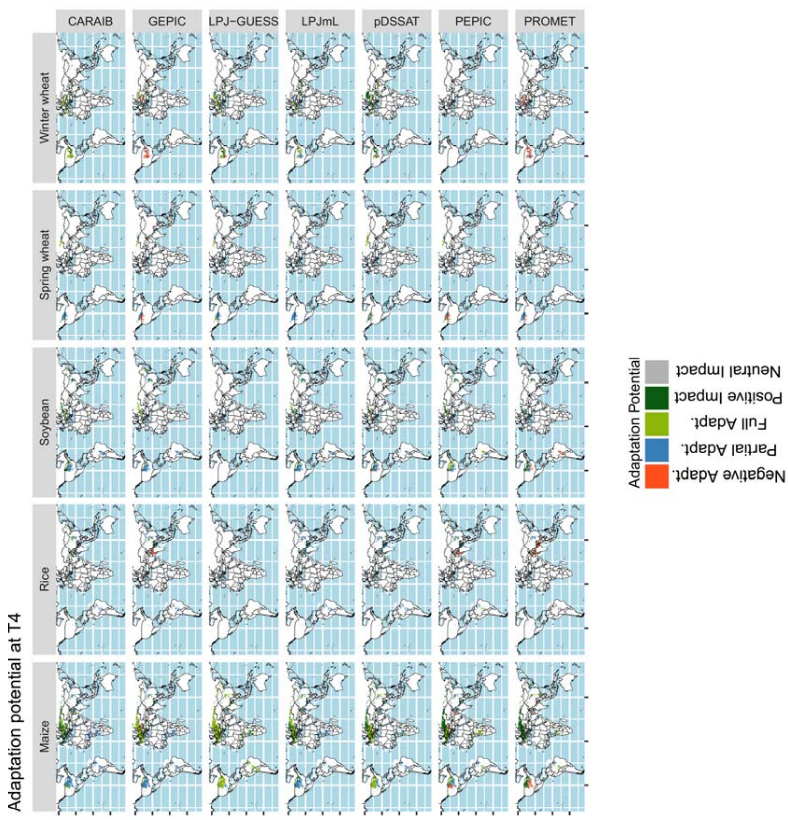


Figure S14: As Figure 4a, but for each GGCM.

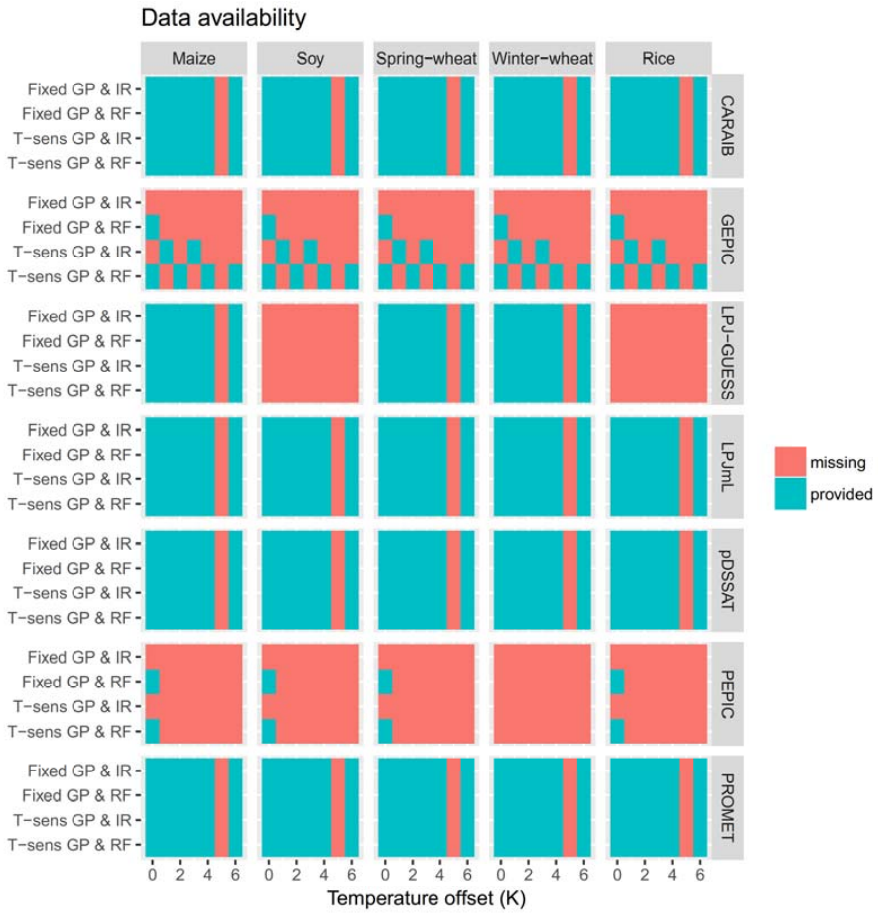


Figure S15: Available crop model simulations at CO_2 mixing ratio of 660 ppm for each model, crop, temperature offset and management setting used in this study. Simulation setups missing (except for LPJ-GUESS rice, LPJ-GUESS soy, GEPIC all crops and PEPIC all crops) are interpolated as described in Section 2.2.2.

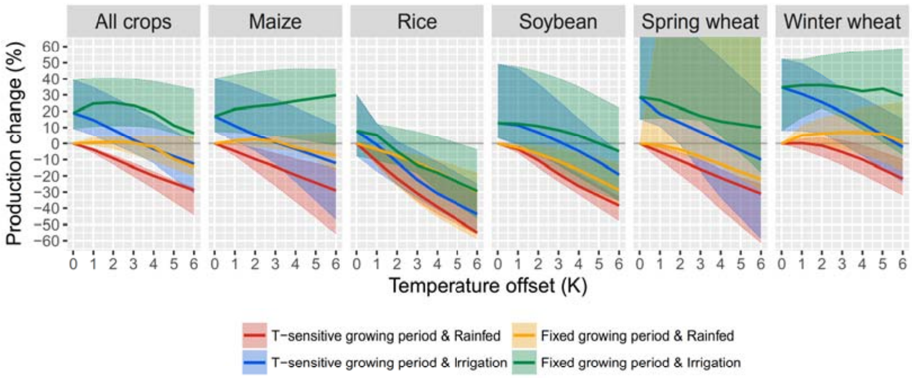


Figure S16: Adaptation at CO_2 mixing ratio of 360 ppm. As Figure 3, but for a subset of GGCMs that provided also the full set of simulations at CO_2 mixing ratio of 660 ppm. To be compared to Figure S17.

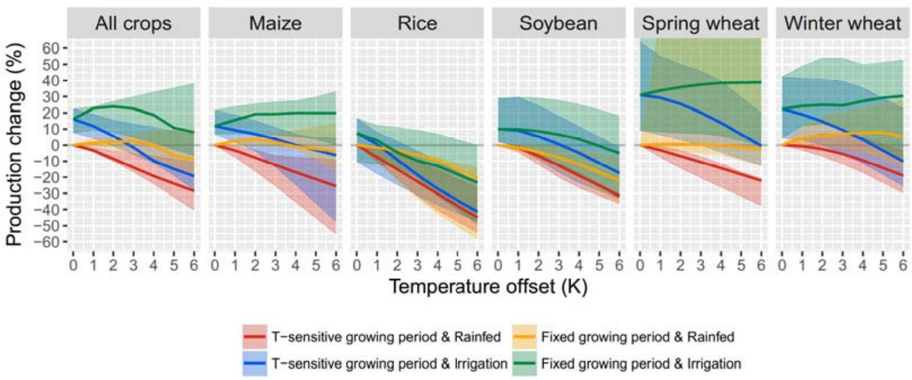


Figure S17: Adaptation at CO_2 mixing ratio of 660 ppm. As Figure 3, but for a subset of GGCMs that provided also the full set of simulations at CO_2 mixing ratio of 660 ppm. To be compared to Figure 16.

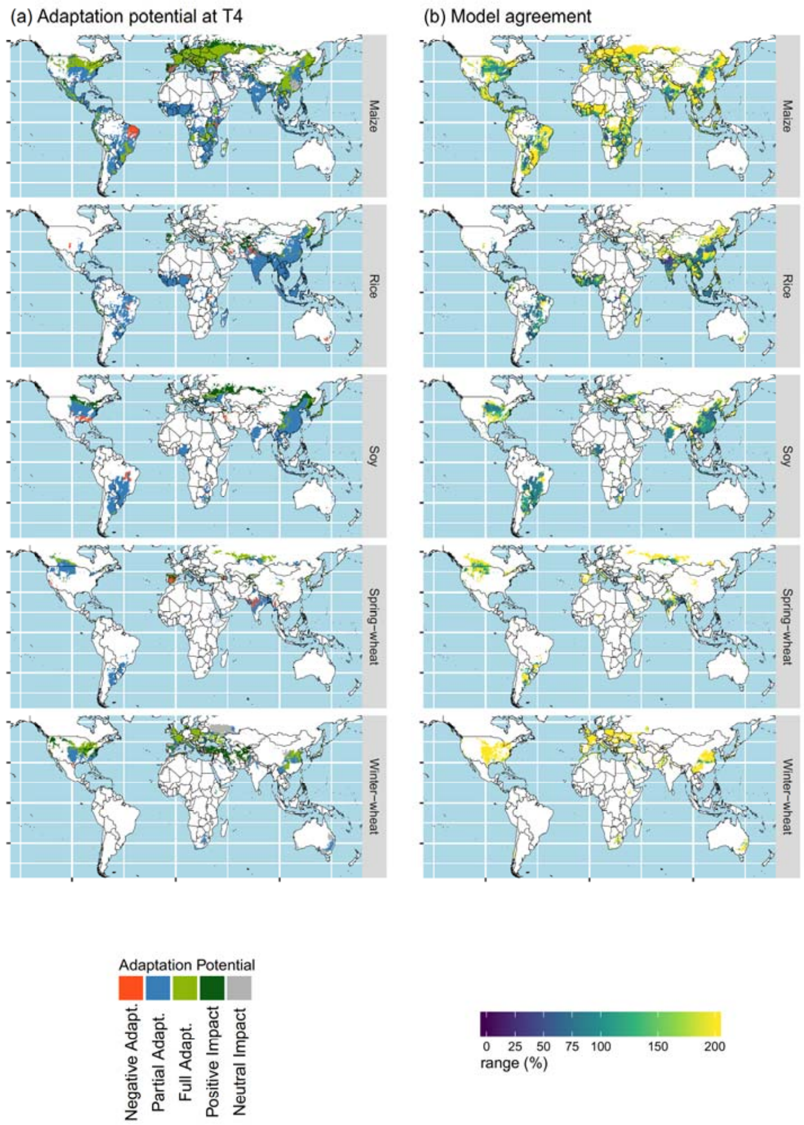


Figure S18: As Figure 4a but at CO_2 mixing ratio of 660 ppm.

B

Supplementary Information for Chapter 3

Modelling cropping periods of grain crops at the global scale

Section A: Illustration of the maturity date rule

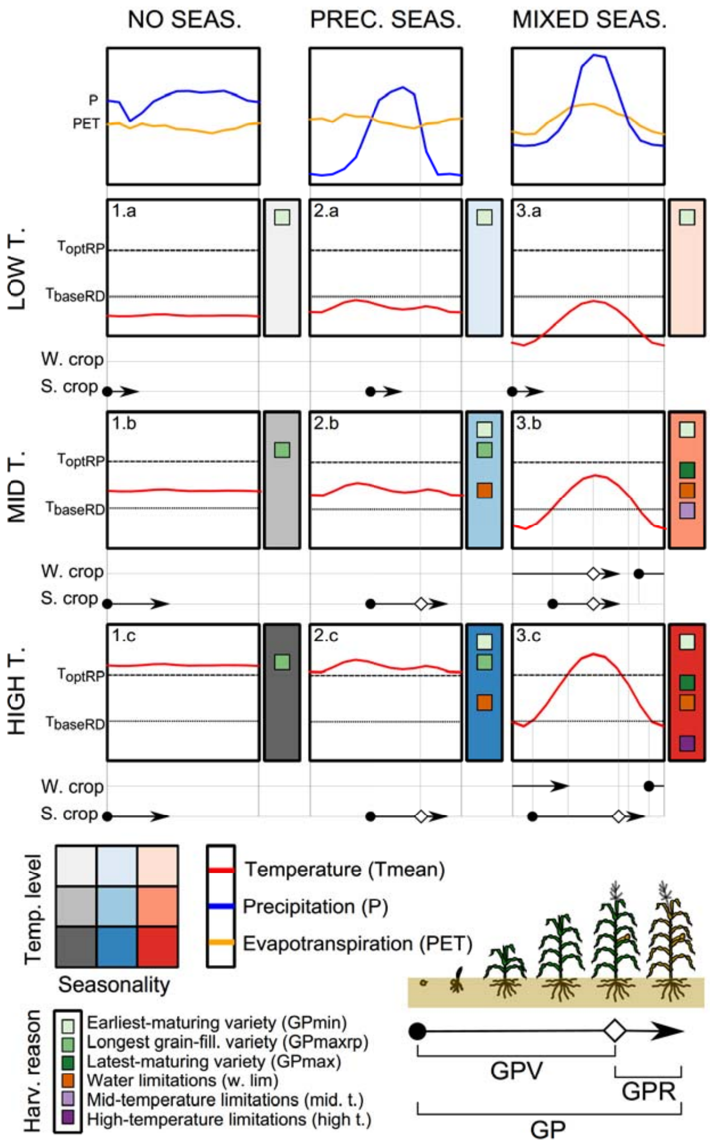


Figure A1: Illustration of the conceptual model and the set of rules to model the harvest date. The different agro-climatic zones are derived by combining seasonality types (Seasonality) and temperature levels (Temp. level); NO SEAS. is no-seasonality, PREC. SEAS is precipitation seasonality only, MIXED SEAS. is temperature AND/OR precipitation seasonality defined as in Waha et al. (2012). Temperature levels are defined based on the temperature of the warmest month of the year; LOW T. is low temperature ($max(T_{mean}) \leq T_{baseRD}$, in fact reproductive production not possible), MID T. is mid temperature ($max(T_{mean}) > T_{baseRD}$ AND $max(T_{mean}) \leq T_{optRP}$, suitable temperatures for reproductive production), HIGH T. is high temperature ($max(T_{mean}) > T_{optRP}$, supra-optimal temperatures for reproductive production). W. crop is winter crop, S. crop is spring crop. T_{mean} is the monthly mean temperature, T_{baseRD} is the base temperature for reproductive development, T_{optRP} is the optimum temperature for reproductive production. GP is the total growing period of the crop (days), GPV is the vegetative phase duration (days), GPR is the reproductive phase duration (days). Harv. reason is the event that can trigger the harvest of a crop within an agro-climatic zone.

2

Section B: Observed growing periods

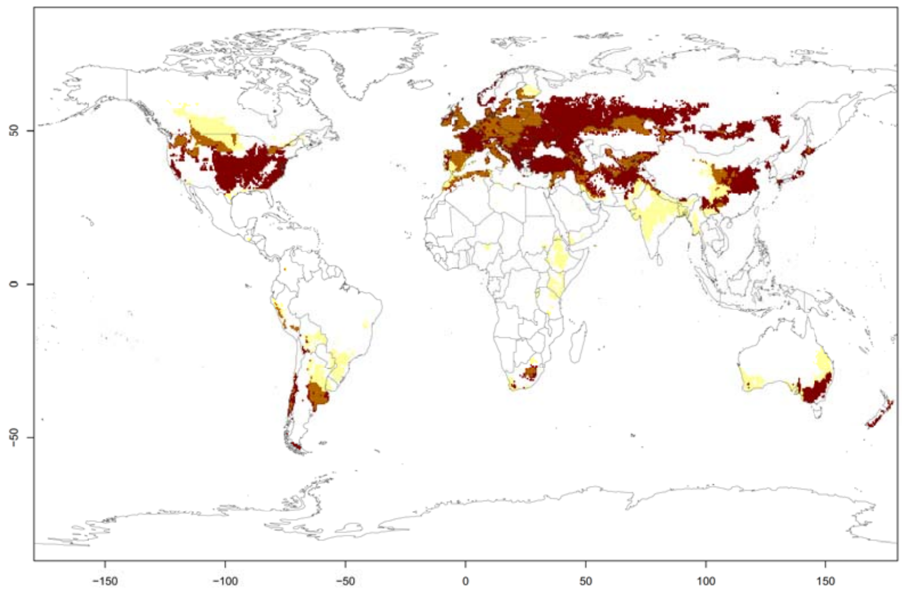
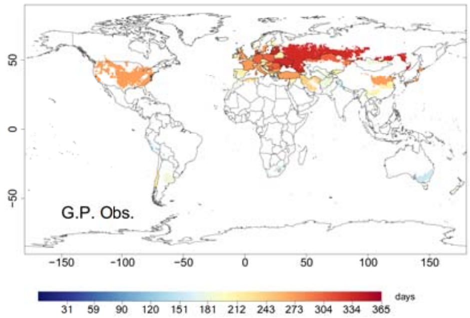
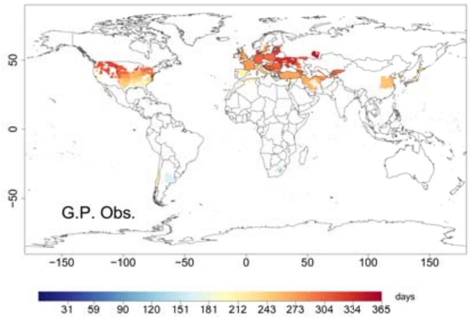


Figure B1: Winter-wheat (brown) and spring-wheat (yellow) growing areas. The total area includes sub-crops 1 and 2 from the MIRCA2000 datasets. Wheat is classified as winter-type if (i) the cropping period includes the coldest month of the year, and (ii) the mean temperature of the coldest month is lower than 10°C

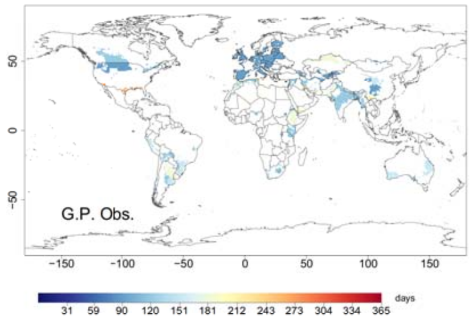
Section B: Observed growing periods



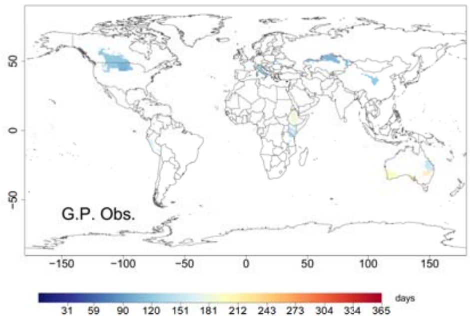
MIRCA2000, winter-wheat



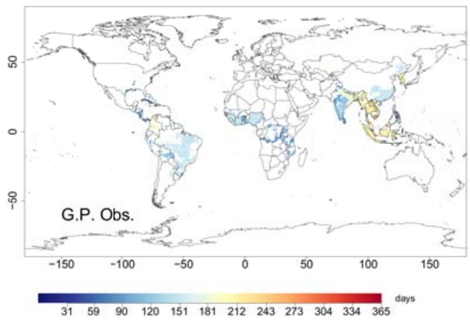
SAGE, winter-wheat



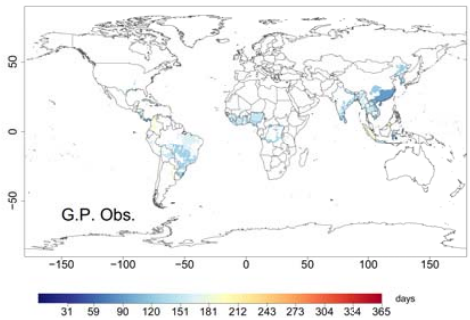
MIRCA2000, spring-wheat



SAGE, spring-wheat



MIRCA2000, rice



SAGE, rice

3

Section B: Observed growing periods

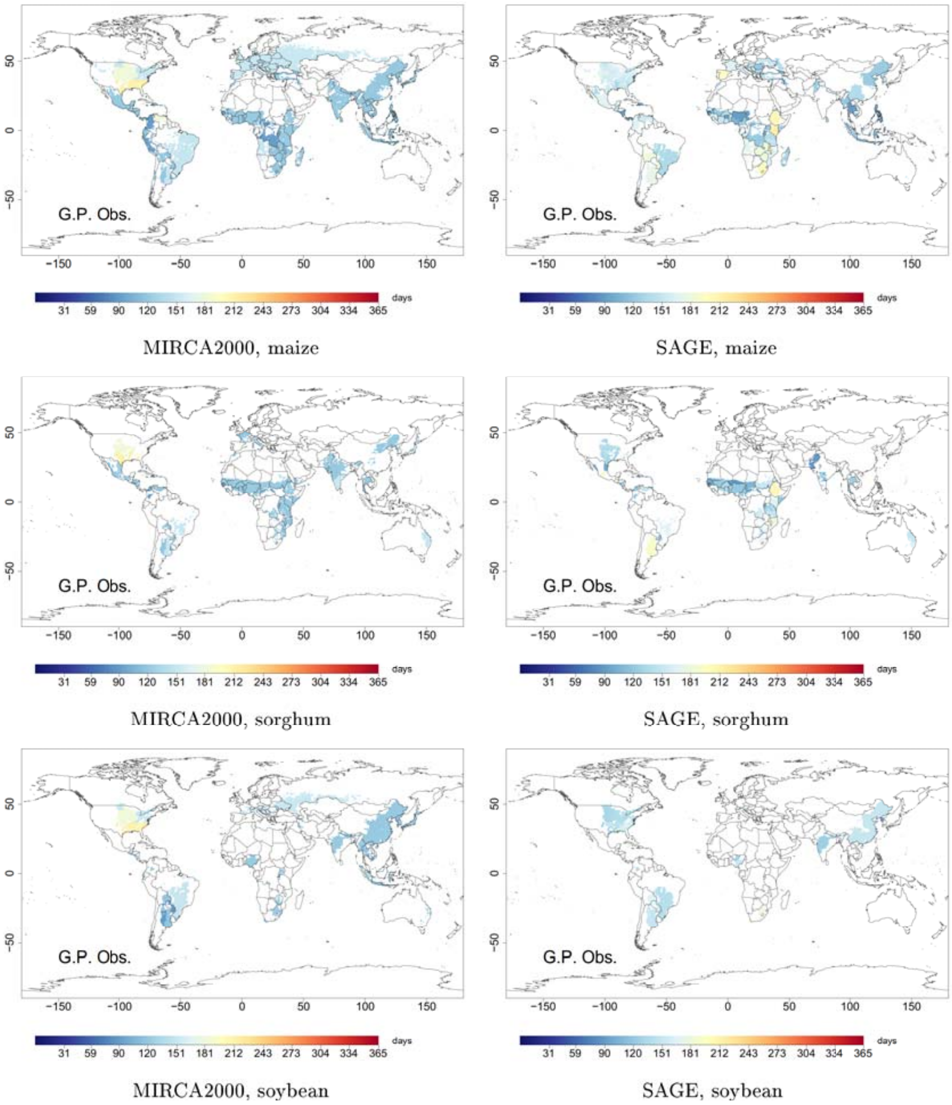


Figure B2: Comparison beteween MIRCA2000 (left column) and SAGE (right column) of reported growing period (sowing-to-maturity, GP) lengths (days)

Section C: PPET_{ratio} and $\text{PPET}_{ratioDIFF}$ analysis

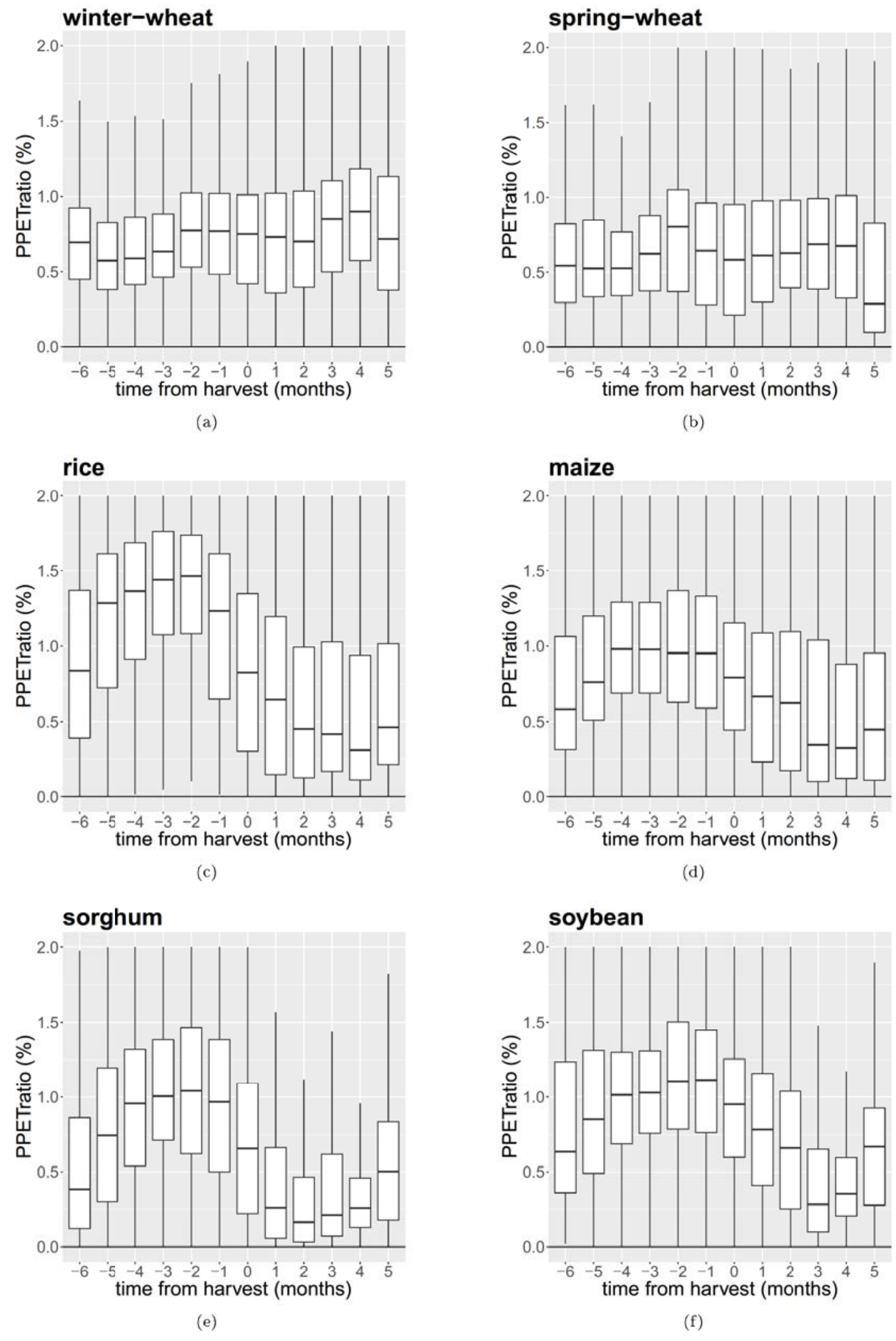


Figure C1: Box plot of the PPETratio evolution across the crop growing periods. The x-axes represents the time from harvest (month), the y-axes represents the PPETratio of that month. Each box represents all grid cells of the cultivated area of a crop. PPETratio of each month has been computed (Eq. 1) from the AgMERRA climate dataset (Ruane et al., 2015).

2

Section C: PPET$_{ratio}$ and PPET$_{ratioDIFF}$ analysis

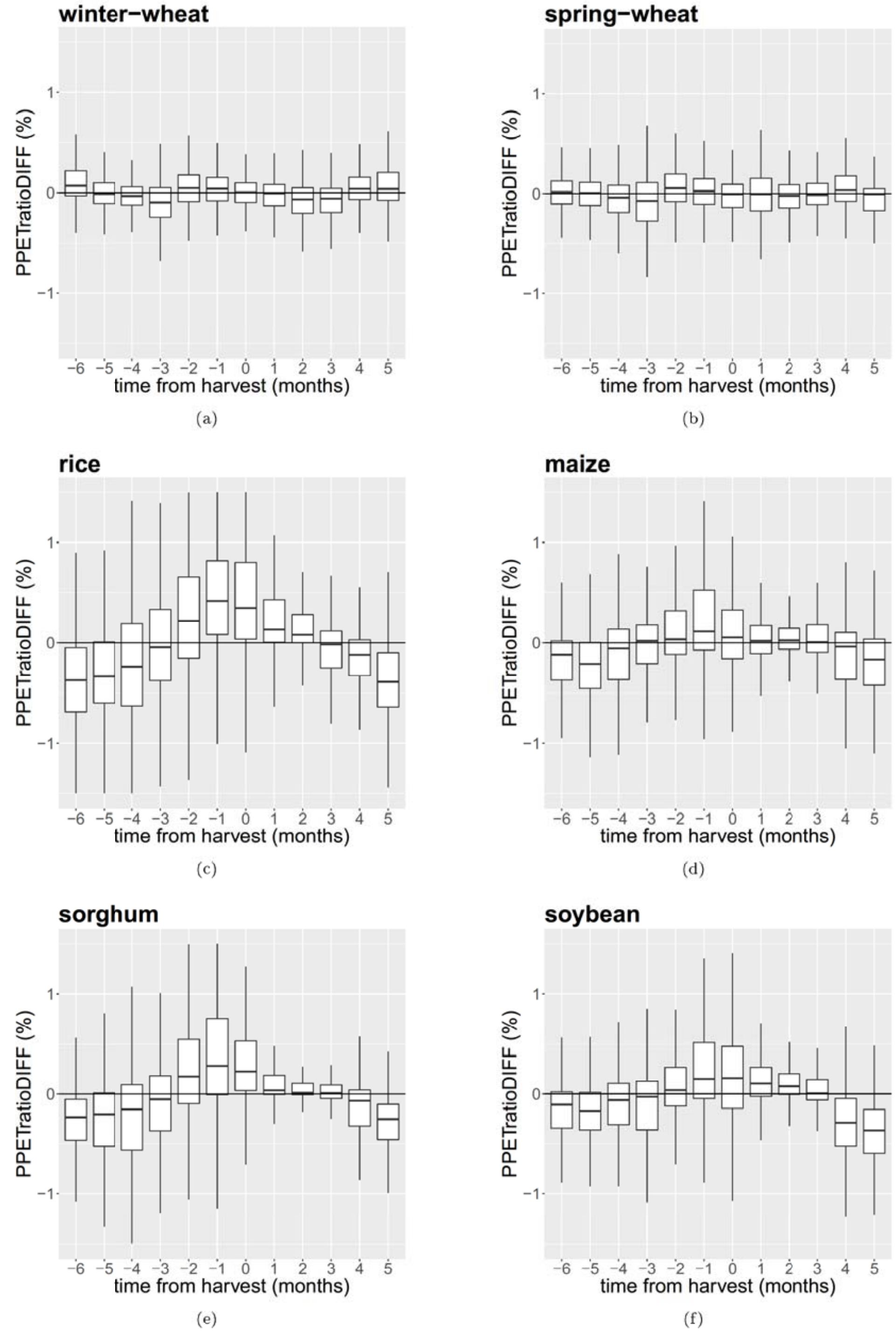


Figure C2: Box plot of the PPETratioDIFF evolution across the crop growing periods. The x-axes represents the time from harvest (month), the y-axes represents the PPETratioDIFF of that month. Each box represents all grid cells of the cultivated area of a crop. PPETratioDIFF of each month has been computed (Eq. 2) from the AgMERRA climate dataset (Ruane et al., 2015).

3

Section C: PPET$_{ratio}$ and PPET$_{ratioDIFF}$ analysis

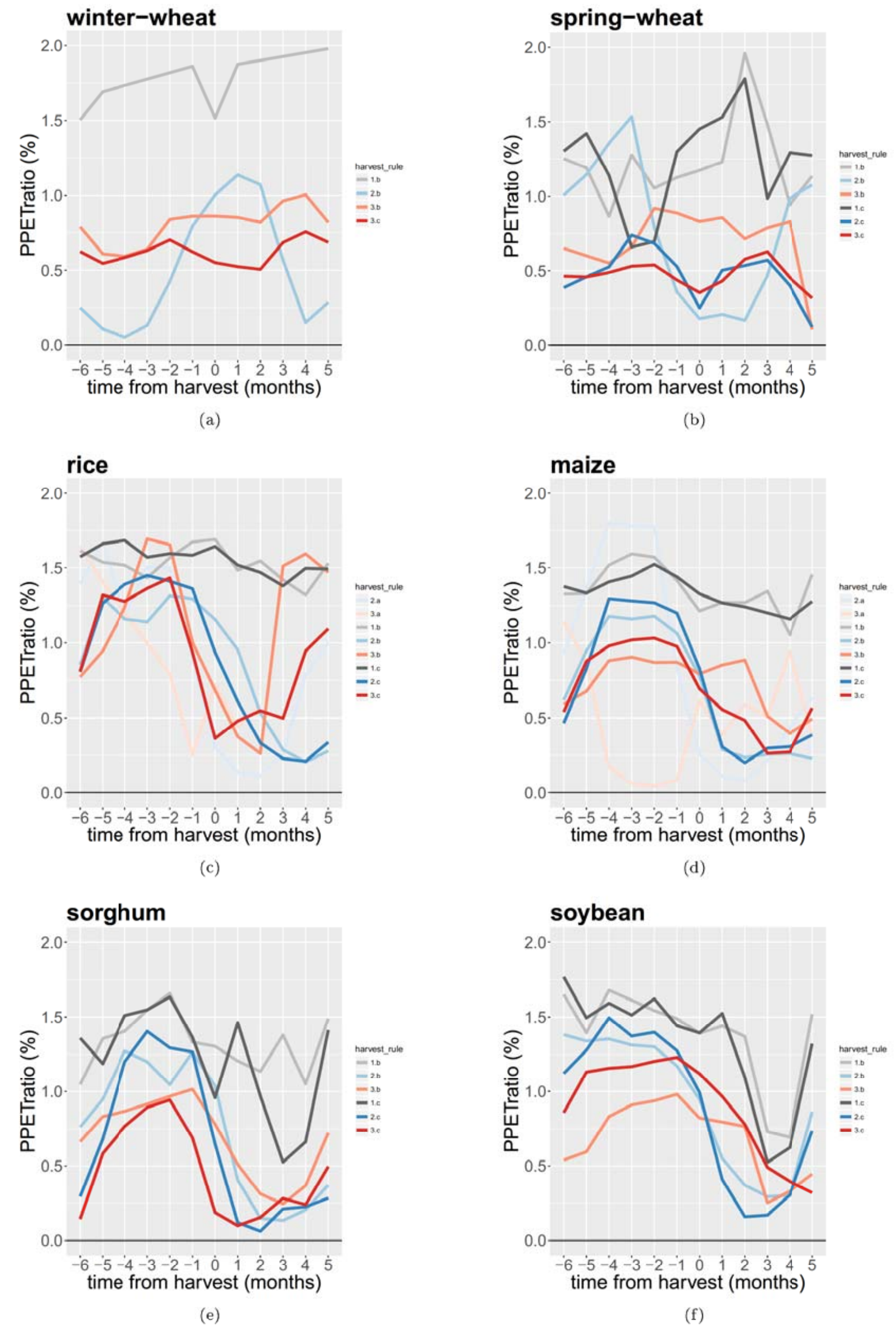
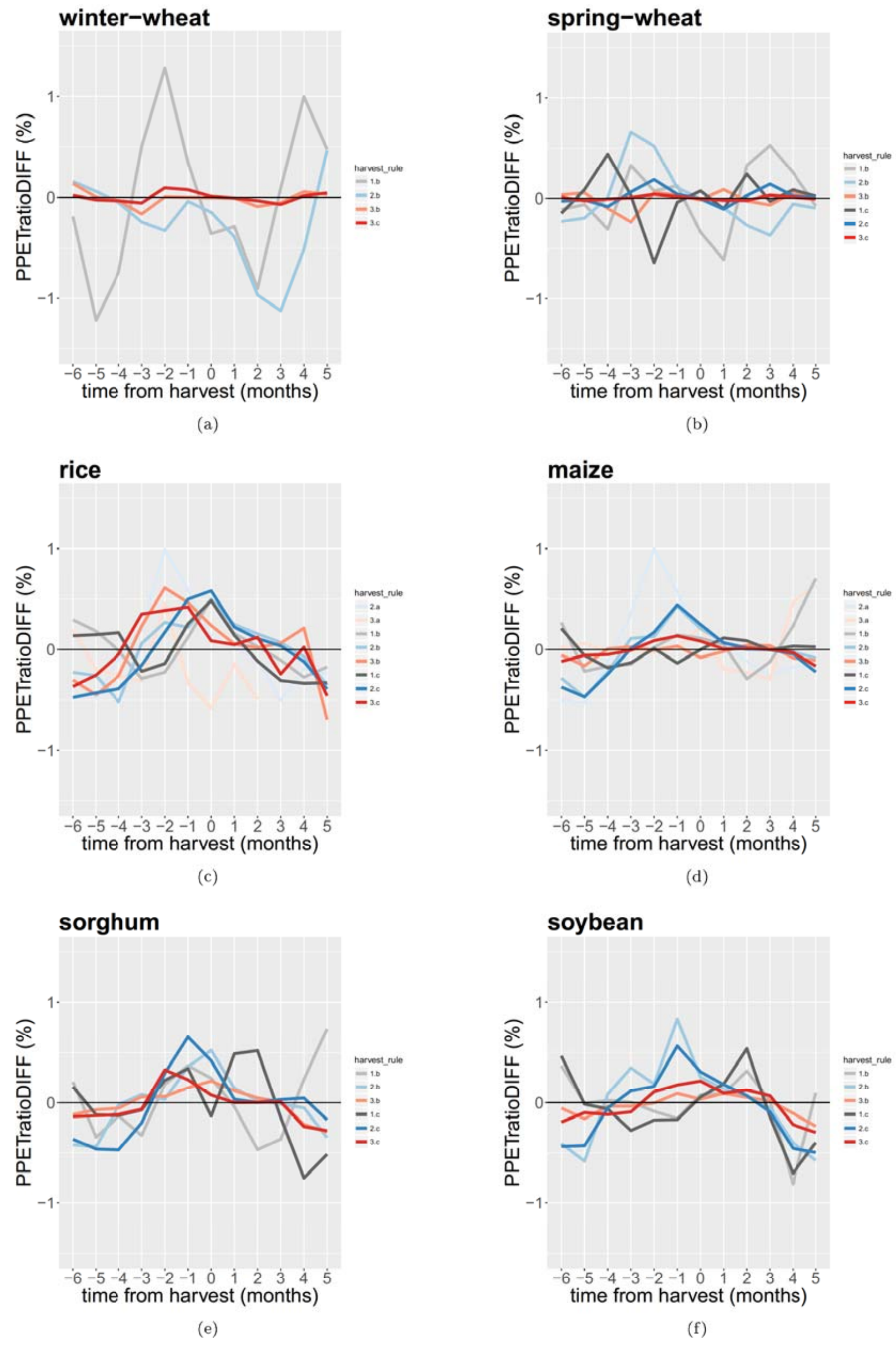


Figure C3: Plot of the PPETratio evolution across the crop growing periods by agro-climatic zone. The x-axes represents the time from harvest (month), the y-axes represents the PPETratio of that month. Each line represents the average across all grid cells of the cultivated area of a crop and agro-climatic zone. PPETratio of each month has been computed (Eq. 1) from the AgMERRA climate dataset (Ruane et al., 2015).

4

Section C: $PPET_{ratio}$ and $PPET_{ratioDIFF}$ analysis



(a) (b) (c) (d) (e) (f)

Figure C4: Plot of the PPETratioDIFF evolution across the crop growing periods by agro-climatic zone. The x-axes represents the time from harvest (month), the y-axes represents the PPETratioDIFF of that month. Each line represents the average across all grid cells of the cultivated area of a crop and agro-climatic zone. PPETratioDIFF of each month has been computed (Eq. 2) from the AgMERRA climate dataset (Ruane et al., 2015).

5

Section D: Sensitivity analysis

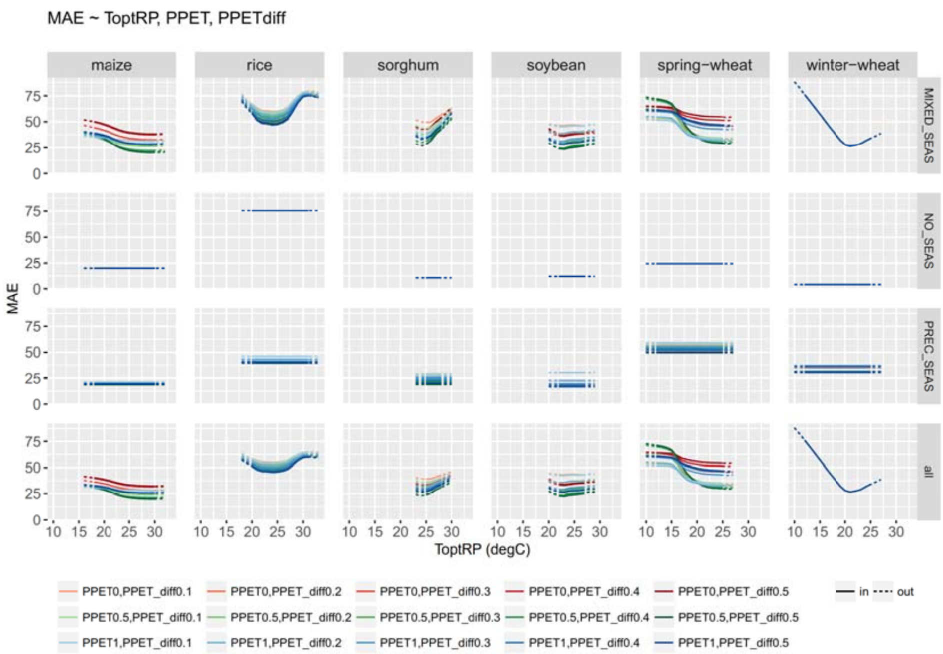


Figure D1: Sensitivity analysis. Effect of the variation of the optimum temperature for reproductive production (T_{optRP}), of the absolute precipitation to potential evapotranspiration ration ($PPET_{ratio}$) and of the relative precipitation to potential evapotranspiration ration ($PPET_{ratioDIFF}$) parameters on the model performance. MAE is the mean absolute error of the harvest date, considering difference with MIRCA2000.

	crop	crop_seasonality	mae	temp_opt_rp	p_pet_ratio	p_pet_ratio_diff
1	winter−wheat	all	26.42900	21	NA	NA
2	spring−wheat	all	29.79057	25	0.5	0.5
3	rice	all	45.44591	24	1.0	0.5
4	maize	all	19.76120	29	0.5	0.5
5	sorghum	all	23.65450	25	0.5	0.5
6	soybean	all	22.25834	23	0.5	0.5

Figure D2: Sensitivity analysis. Best performing (minimum MAE) parameter setting: combination of the optimum temperature for reproductive production (T_{optRP}), the absolute precipitation to potential evapotranspiration ratio ($PPET_{ratio}$) and the relative precipitation to potential evapotranspiration ratio ($PPET_{ratioDIFF.}$). MAE is the mean absolute error of the harvest date, considering difference with MIRCA2000.

2

Section E: Aggregated model performances

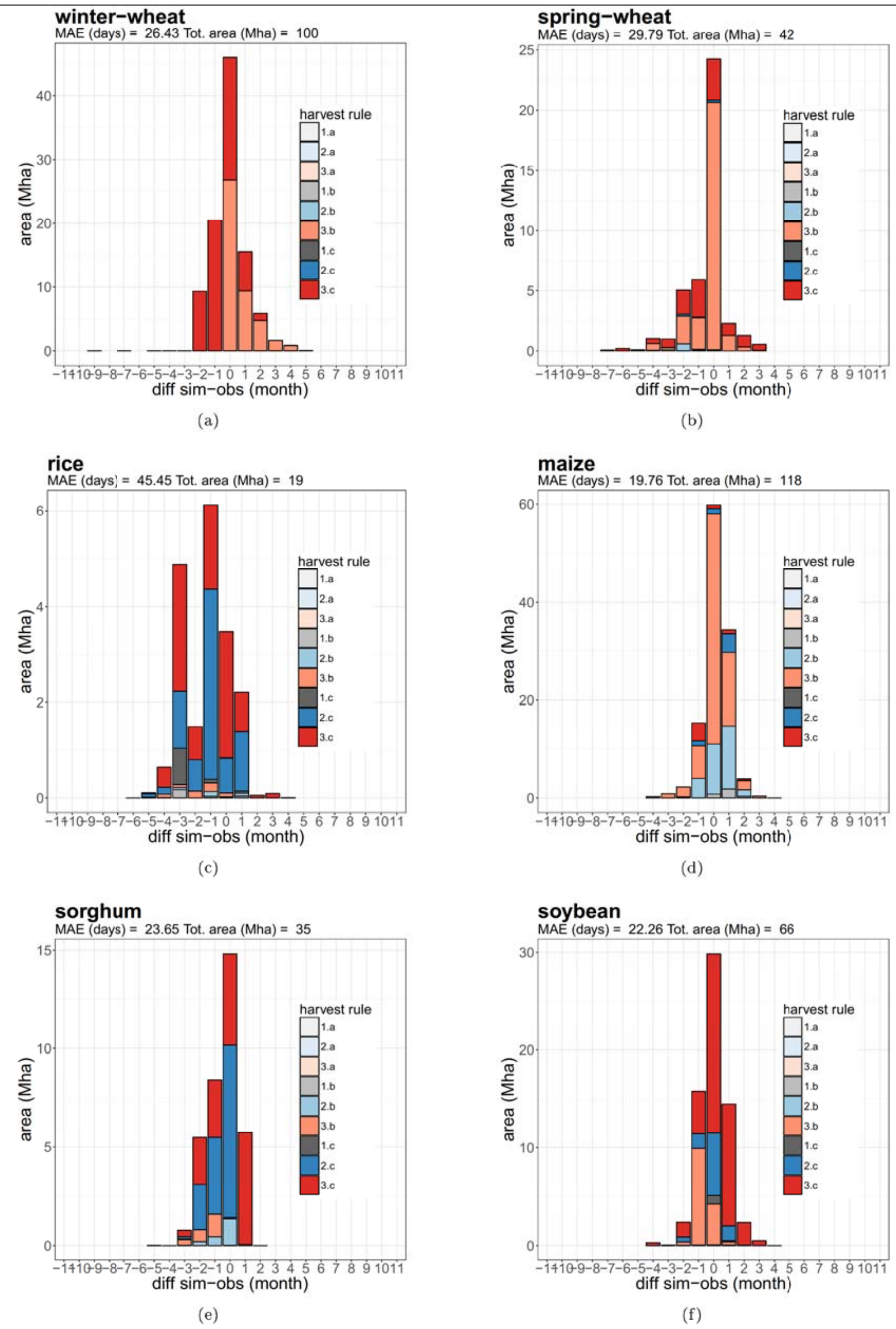


Figure E1: Aggregated performances of the model to compute the maturity dates. The bar plot shows the frequency distribution of the difference between simulated and observed (MIRCA2000) harvest dates. The frequency is measured in terms of harvested area (Mha), the sum of all bars is the total area (Mha) of the crop reported by MIRCA2000. The colors indicate the different realized harvest reasons: the choice of the earliest-maturing cultivar (GP_{min}); the cultivar with the longest grain-filling phase (GP_{maxrp}); the latest-maturing cultivar (GP_{max}); or the occurrence of water limitations ($w.\ lim.$); mid-temperature limitations ($mid.\ t.$); high-temperature limitations ($high\ t.$). MAE is the area weighted mean absolute error (days, Eq. 10) for the crop.

Section E: Aggregated model performances

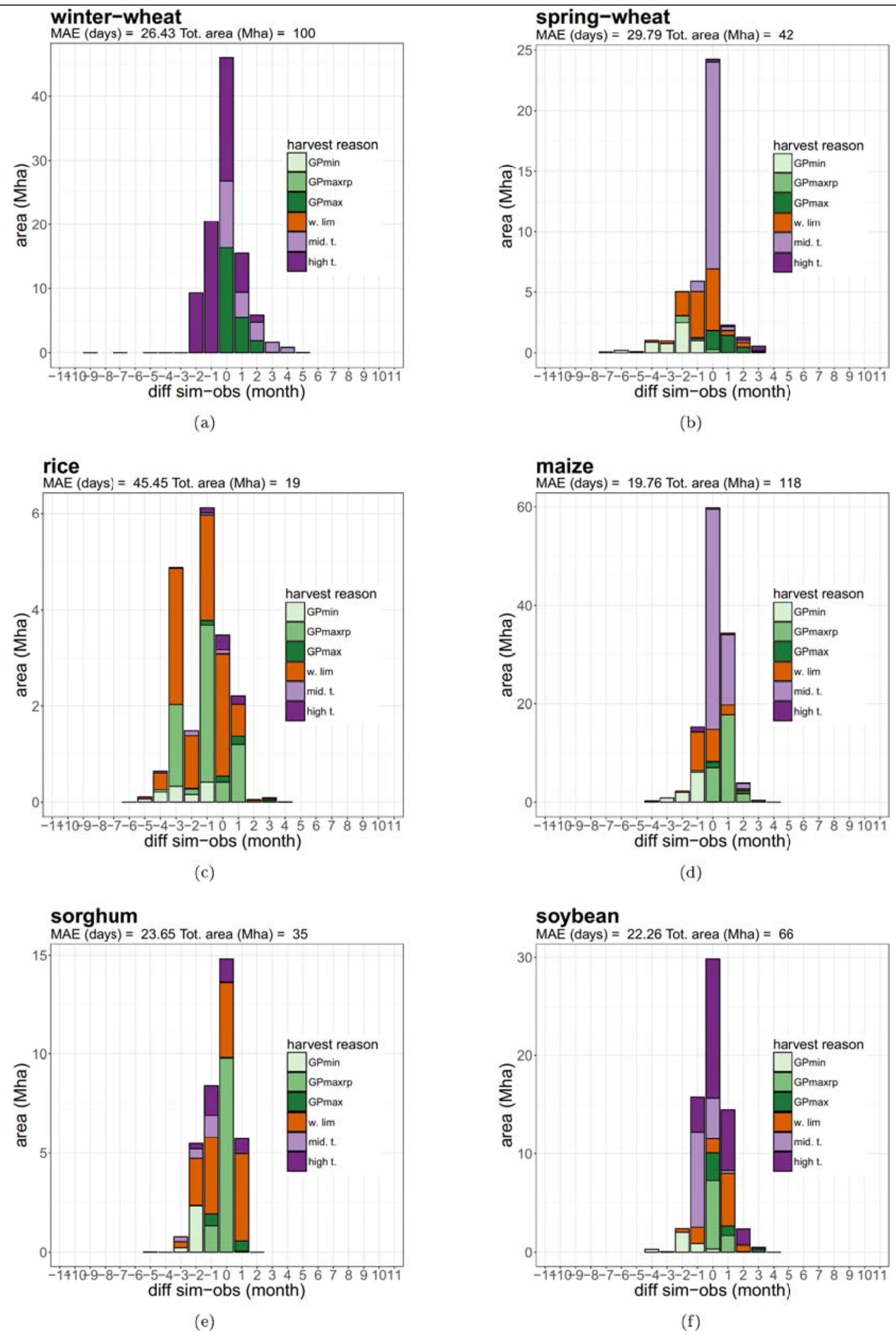


Figure E2: Aggregated performances of the model to compute the maturity dates. The bar plot shows the frequency distribution of the difference between simulated and observed (MIRCA2000) harvest dates. The frequency is measured in terms of harvested area (Mha), the sum of all bars is the total area (Mha) of the crop reported by MIRCA2000. The colors indicate the different agro-climatic zones and the corresponding rule (1.a-3.c). MAE is the area weighted mean absolute error (days, Eq. 10) for the crop.

3

Section E: Aggregated model performances

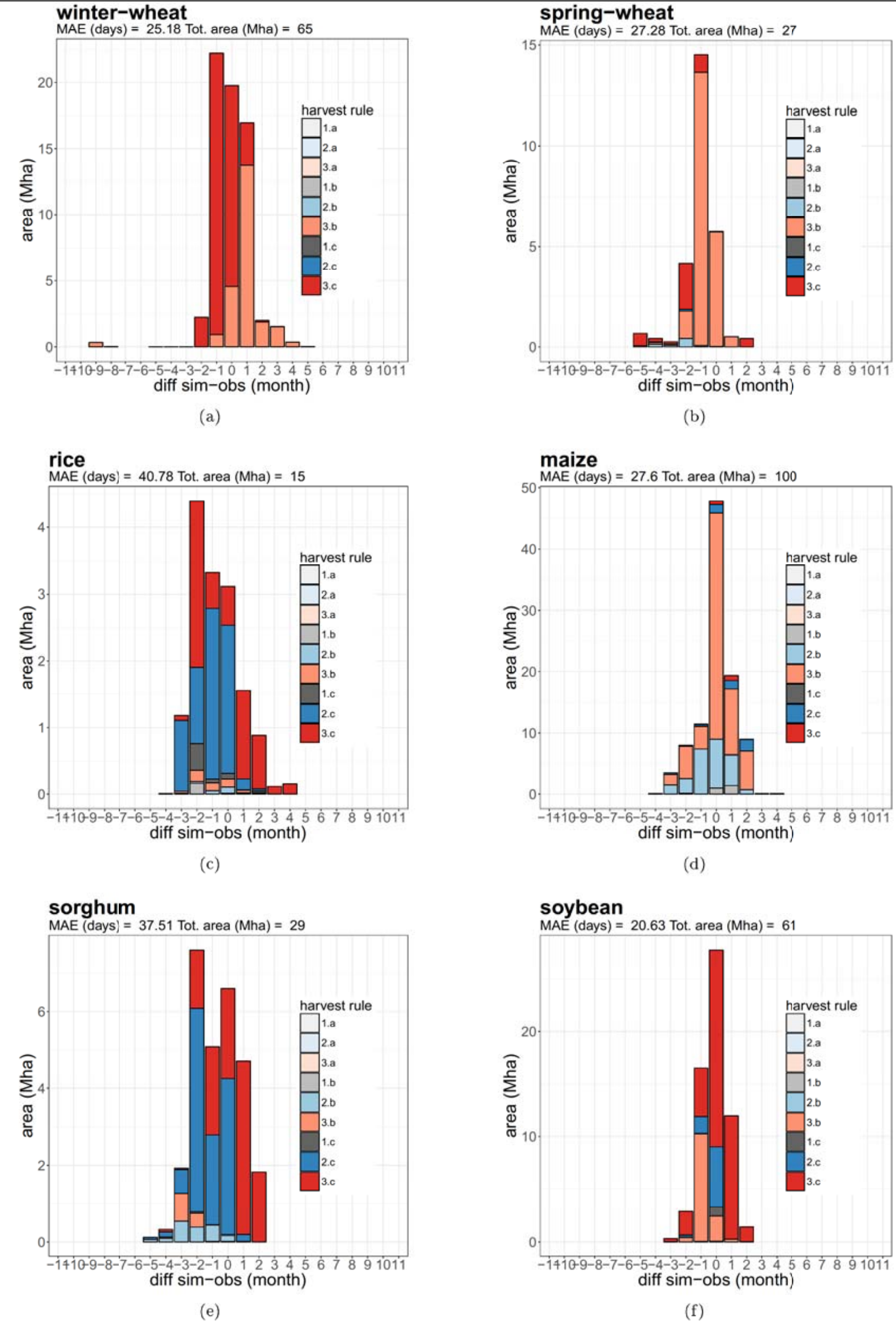


Figure E3: Aggregated performances of the model to compute the maturity dates. The bar plot shows the frequency distribution of the difference between simulated and observed (SAGE) harvest dates. The frequency is measured in terms of harvested area (Mha), the sum of all bars is the total area (Mha) of the crop reported by MIRCA2000 (SAGE does not report crop area). The colors indicate the different realized harvest reasons: the choice of the earliest-maturing cultivar (GP_{min}); the cultivar with the longest grain-filling phase (GP_{maxrp}); the latest-maturing cultivar (GP_{max}); or the occurrence of water limitations ($w.\ lim.$); mid-temperature limitations ($mid.\ t.$); high-temperature limitations ($high\ t.$). MAE is the area weighted mean absolute error (days, Eq. 10) for the crop.

Section E: Aggregated model performances

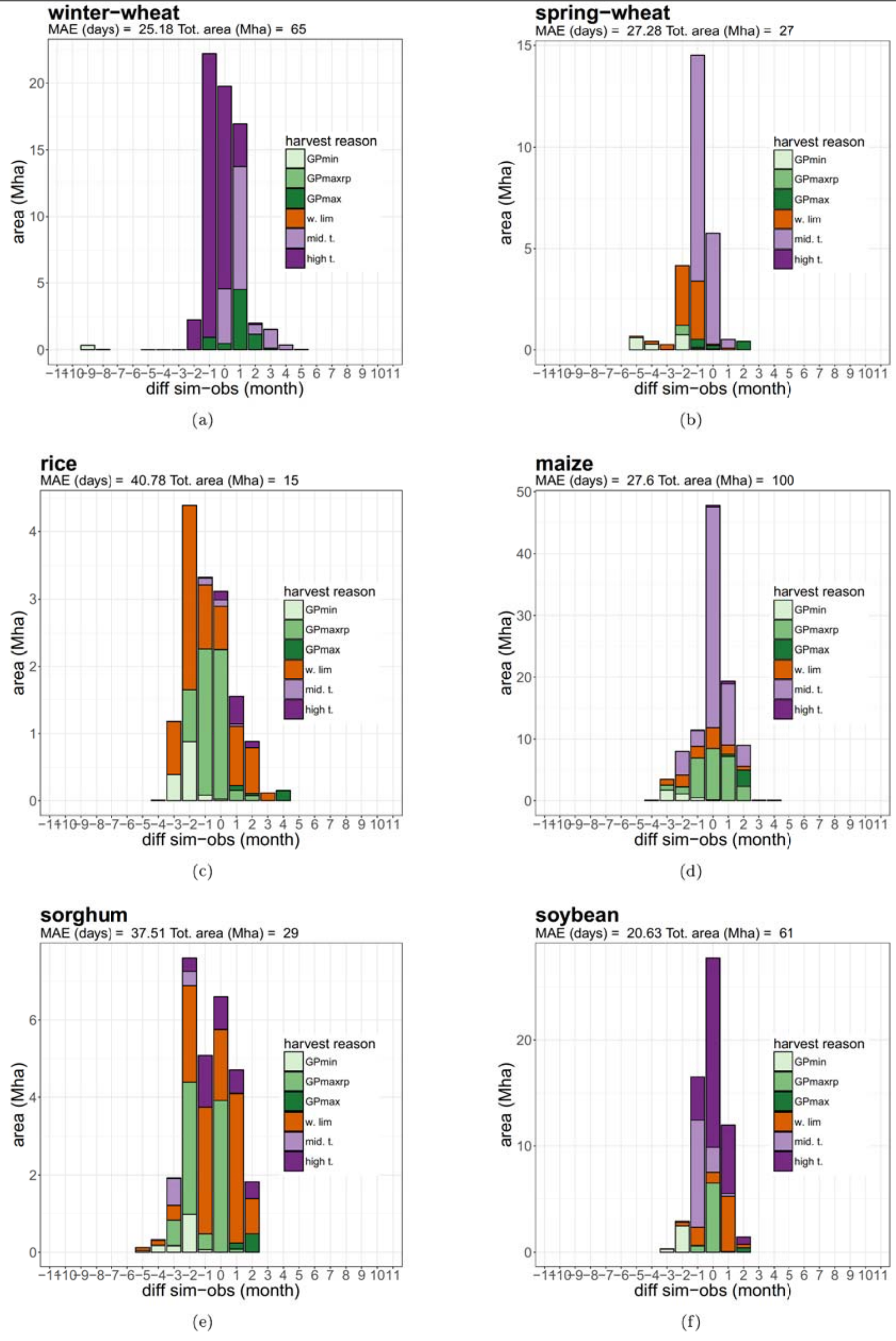


Figure E4: Aggregated performances of the model to compute the maturity dates. The bar plot shows the frequency distribution of the difference between simulated and observed (SAGE) harvest dates. The frequency is measured in terms of harvested area (Mha), the sum of all bars is the total area (Mha) of the crop reported by MIRCA2000 (SAGE does not report crop area). The colors indicate the different agro-climatic zones and the corresponding rule (1.a-3.c). MAE is the area weighted mean absolute error (days, Eq. 10) for the crop.

5

Section F: Global maps of computed harvest dates for all crops (MIRCA2000 sowing dates prescribed)

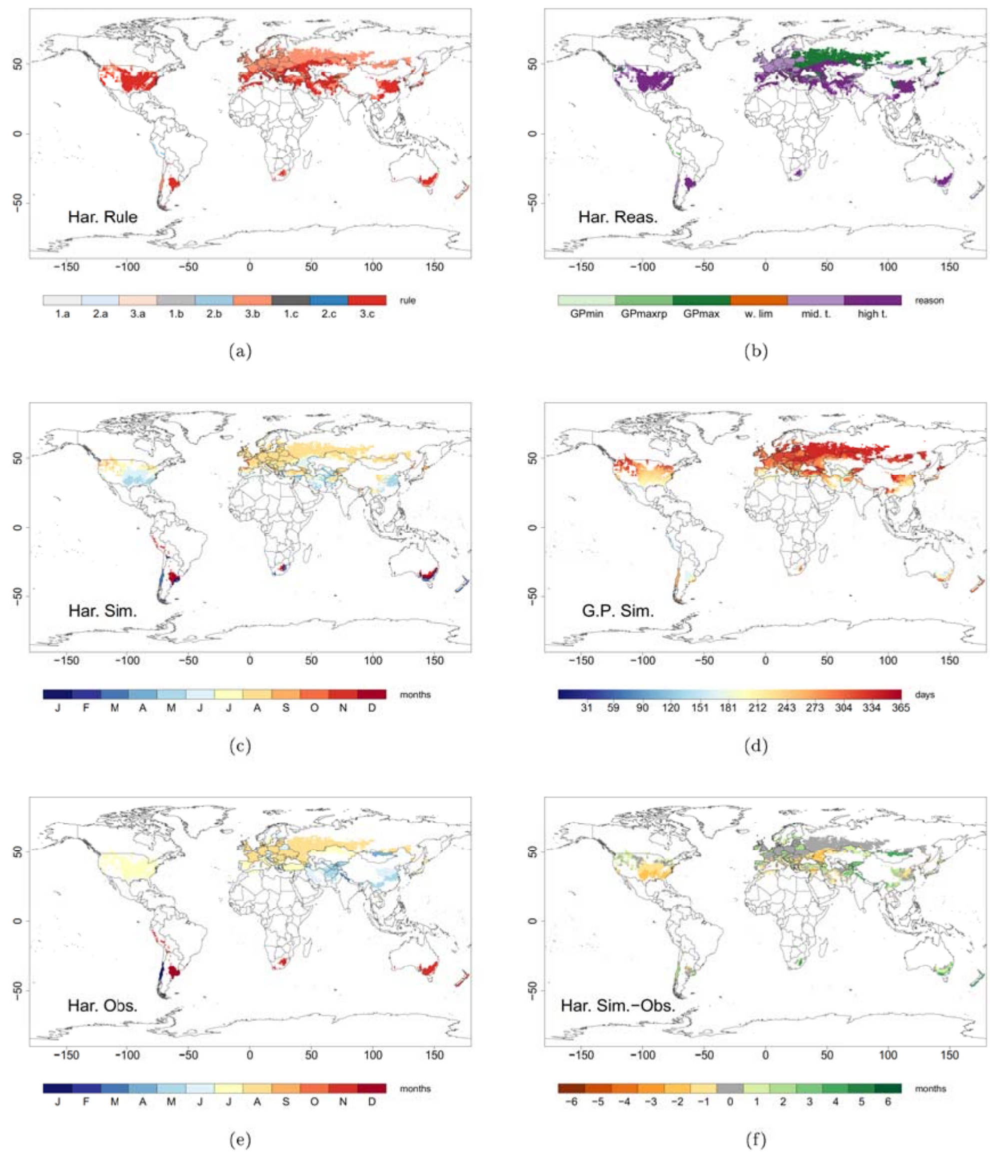


Figure F1: Results of the modelling workflow phases and evaluation for winter-wheat (a) agro-climatic zones of cultivation and corresponding rule applied for computing the harvest date (1.a-3.c); (b) realized harvest reason, representing the factor causing the end of the growing period (GP_{min} is earliest-maturing cultivar; GP_{maxrp} is longest grain-fill cultivar; GP_{max} is latest-maturing cultivar; $w.lim$ is water limitations; *mid t.* is mid-temperature limitations; *hight t.* is high-temperature limitations.); (c); computed harvest month with our modelling approach, where we have prescribed the sowing date from MIRCA2000; (d) length of the computed total growing period (GP, sowing-to-harvest time); (e) observed harvest month from MIRCA2000; (f) difference between computed and observed harvest month. White color indicates pixels with less than 0.001% maize cultivated area according to MIRCA2000.

2

Section F: Global maps of computed harvest dates for all crops (MIRCA2000 sowing dates prescribed)

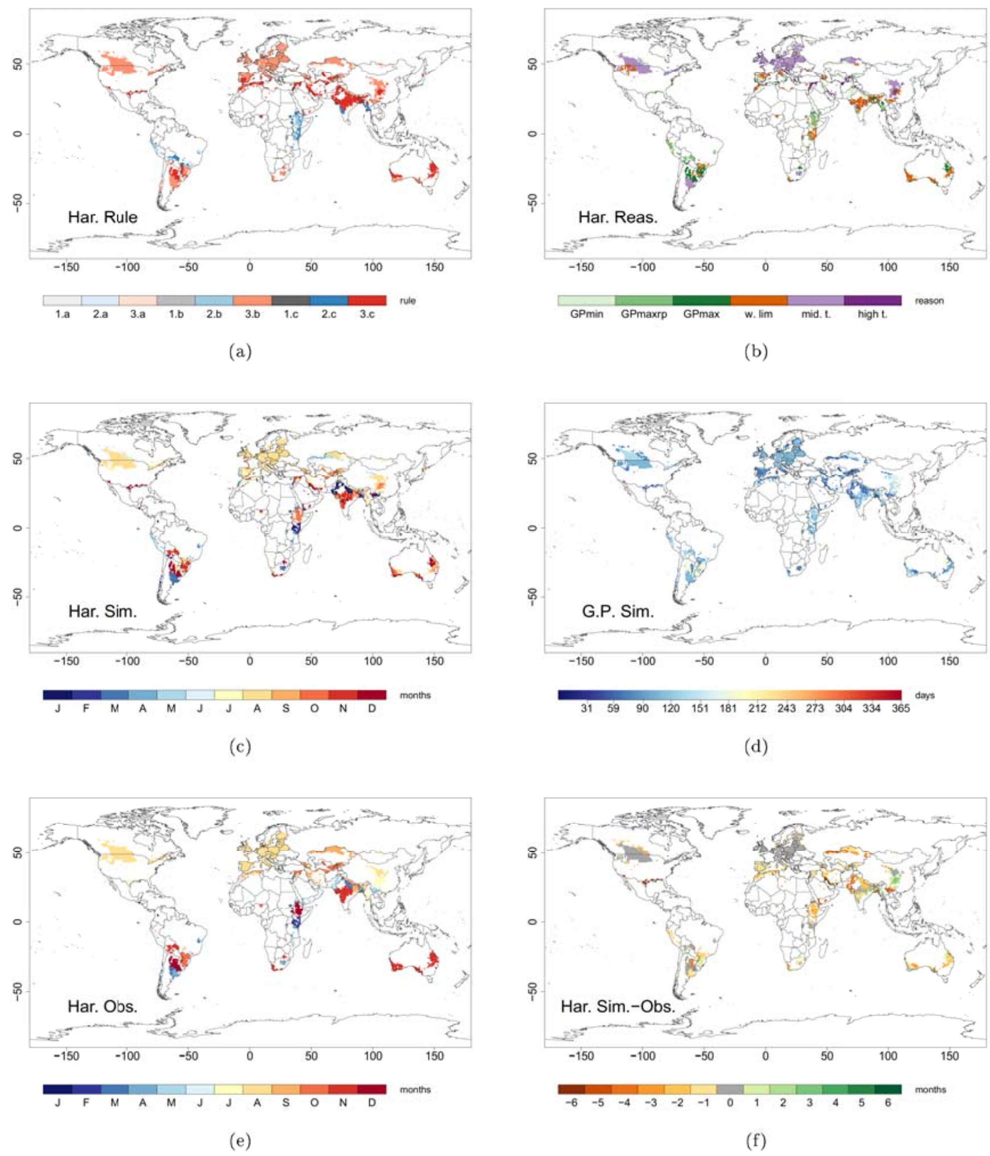


Figure F2: Results of the modelling workflow phases and evaluation for spring-wheat (a) agro-climatic zones of cultivation and corresponding rule applied for computing the harvest date (1.a-3.c); (b) realized harvest reason, representing the factor causing the end of the growing period (GP_{min} is earliest-maturing cultivar; GP_{maxrp} is longest grain-fill cultivar; GP_{max} is latest-maturing cultivar; $w.lim$ is water limitations; *mid t.* is mid-temperature limitations; *hight t.* is high-temperature limitations.); (c); computed harvest month with our modelling approach, where we have prescribed the sowing date from MIRCA2000; (d) length of the computed total growing period (GP, sowing-to-harvest time); (e) observed harvest month from MIRCA2000; (f) difference between computed and observed harvest month. White color indicates pixels with less than 0.001% maize cultivated area according to MIRCA2000.

3

Section F: Global maps of computed harvest dates for all crops (MIRCA2000 sowing dates prescribed)

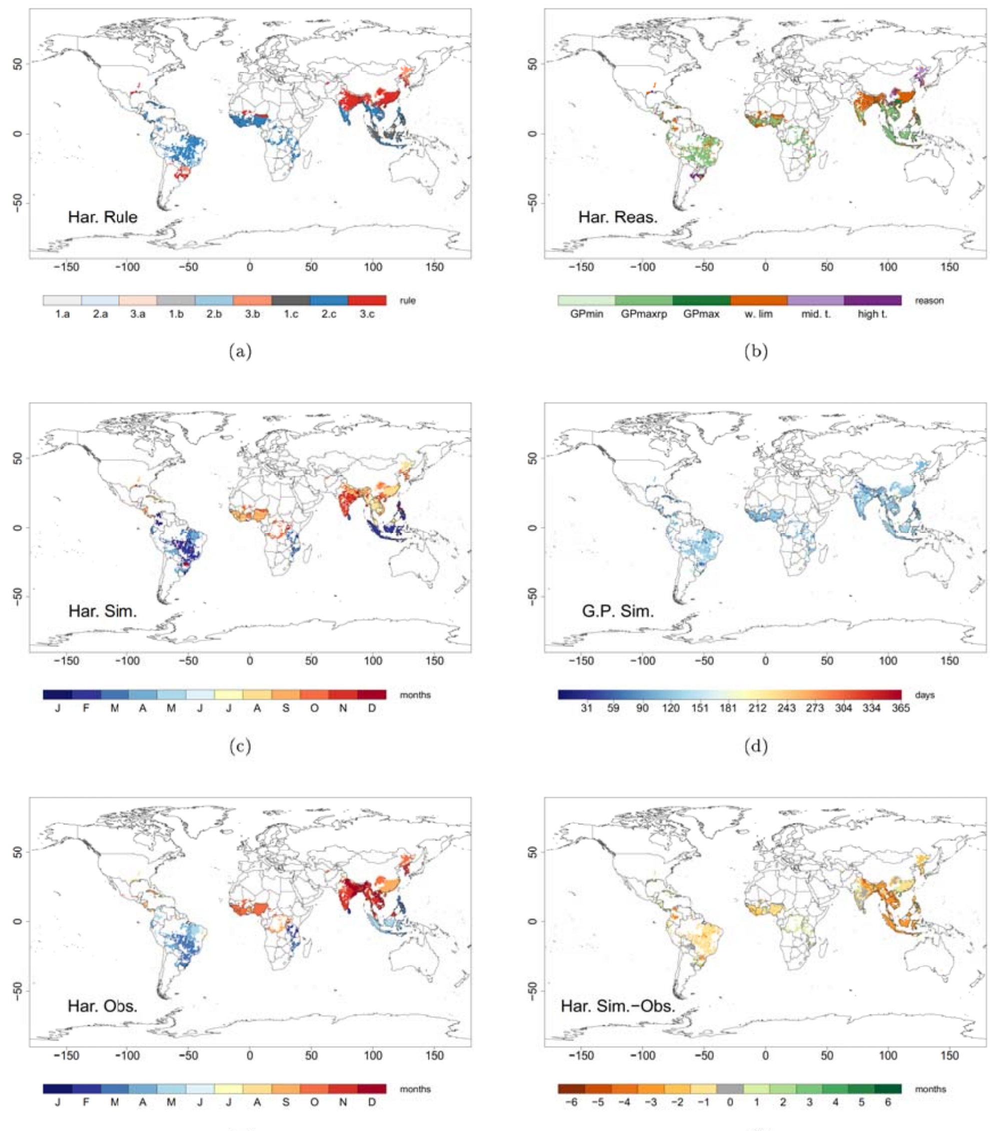


Figure F3: Results of the modelling workflow phases and evaluation for rice (a) agro-climatic zones of cultivation and corresponding rule applied for computing the harvest date (1.a-3.c); (b) realized harvest reason, representing the factor causing the end of the growing period (GP_{min} is earliest-maturing cultivar; GP_{maxrp} is longest grain-fill cultivar; GP_{max} is latest-maturing cultivar; $w.lim$ is water limitations; $mid\ t.$ is mid-temperature limitations; $hight\ t.$ is high-temperature limitations.); (c); computed harvest month with our modelling approach, where we have prescribed the sowing date from MIRCA2000; (d) length of the computed total growing period (GP, sowing-to-harvest time); (e) observed harvest month from MIRCA2000; (f) difference between computed and observed harvest month. White color indicates pixels with less than 0.001% maize cultivated area according to MIRCA2000.

Section F: Global maps of computed harvest dates for all crops (MIRCA2000 sowing dates prescribed)

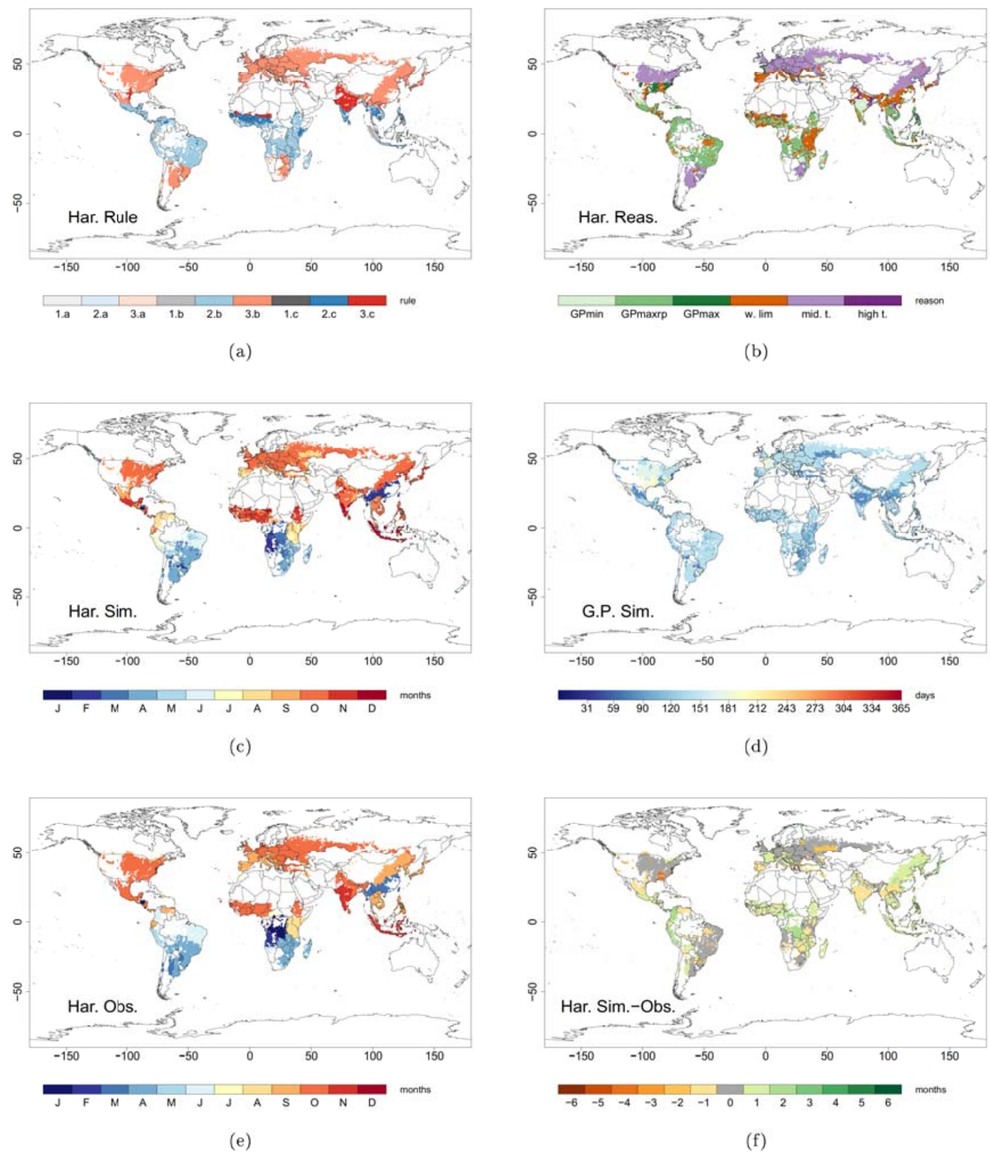


Figure F4: Results of the modelling workflow phases and evaluation for maize (a) agro-climatic zones of cultivation and corresponding rule applied for computing the harvest date (1.a-3.c); (b) realized harvest reason, representing the factor causing the end of the growing period (GP_{min} is earliest-maturing cultivar; GP_{maxrp} is longest grain-fill cultivar; GP_{max} is latest-maturing cultivar; $w.lim$ is water limitations; $mid\ t.$ is mid-temperature limitations; $hight\ t.$ is high-temperature limitations.); (c); computed harvest month with our modelling approach, where we have prescribed the sowing date from MIRCA2000; (d) length of the computed total growing period (GP, sowing-to-harvest time); (e) observed harvest month from MIRCA2000; (f) difference between computed and observed harvest month. White color indicates pixels with less than 0.001% maize cultivated area according to MIRCA2000.

5

Section F: Global maps of computed harvest dates for all crops (MIRCA2000 sowing dates prescribed)

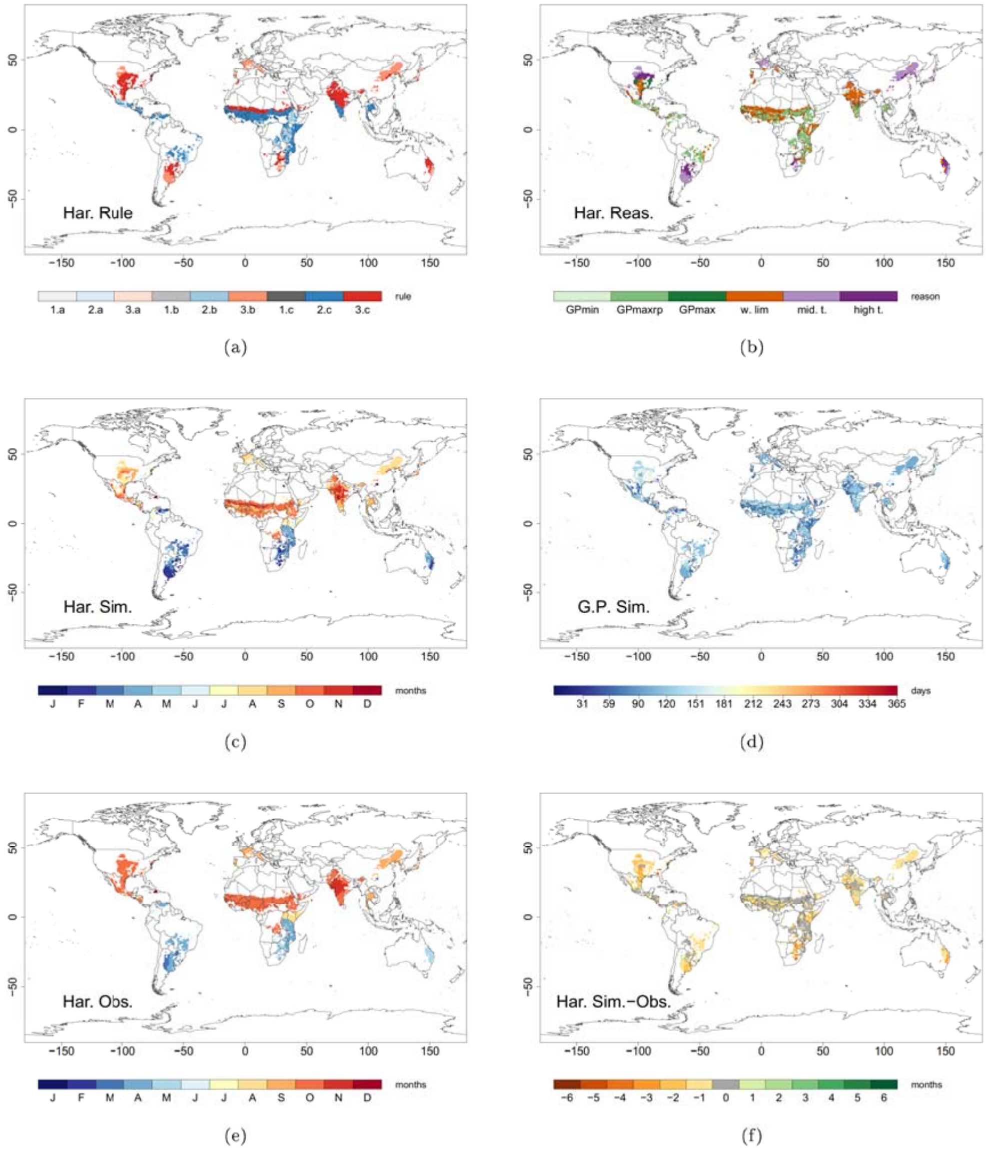


Figure F5: Results of the modelling workflow phases and evaluation for sorghum (a) agro-climatic zones of cultivation and corresponding rule applied for computing the harvest date (1.a-3.c); (b) realized harvest reason, representing the factor causing the end of the growing period (GP_{min} is earliest-maturing cultivar; GP_{maxrp} is longest grain-fill cultivar; GP_{max} is latest-maturing cultivar; *w.lim* is water limitations; *mid t.* is mid-temperature limitations; *hight t.* is high-temperature limitations.); (c); computed harvest month with our modelling approach, where we have prescribed the sowing date from MIRCA2000; (d) length of the computed total growing period (GP, sowing-to-harvest time); (e) observed harvest month from MIRCA2000; (f) difference between computed and observed harvest month. White color indicates pixels with less than 0.001% maize cultivated area according to MIRCA2000.

6

Section F: Global maps of computed harvest dates for all crops (MIRCA2000 sowing dates prescribed)

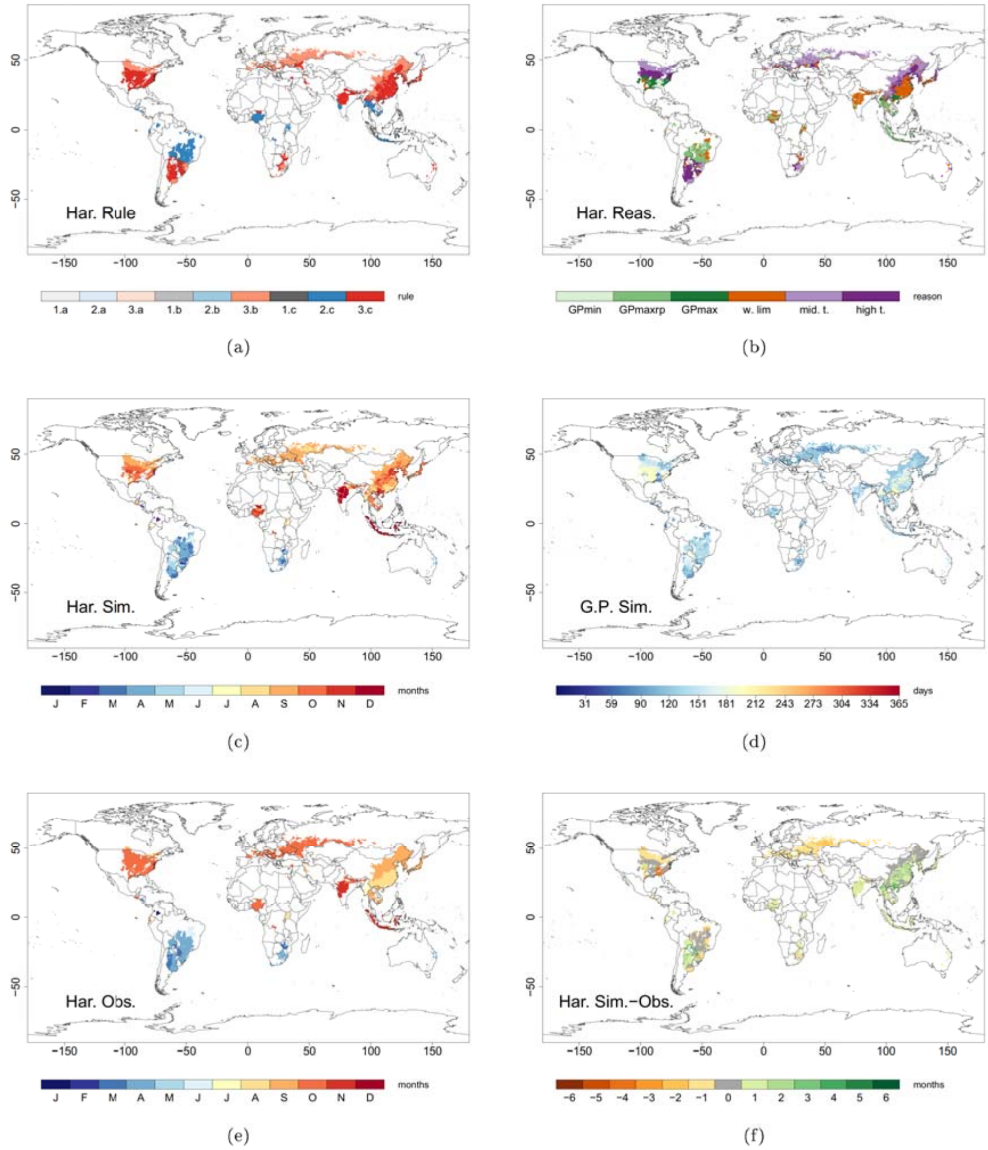


Figure F6: Results of the modelling workflow phases and evaluation for soybean (a) agro-climatic zones of cultivation and corresponding rule applied for computing the harvest date (1.a-3.c); (b) realized harvest reason, representing the factor causing the end of the growing period (GP_{min} is earliest-maturing cultivar; GP_{maxrp} is longest grain-fill cultivar; GP_{max} is latest-maturing cultivar; *w.lim* is water limitations; *mid t.* is mid-temperature limitations; *hight t.* is high-temperature limitations.); (c); computed harvest month with our modelling approach, where we have prescribed the sowing date from MIRCA2000; (d) length of the computed total growing period (GP, sowing-to-harvest time); (e) observed harvest month from MIRCA2000; (f) difference between computed and observed harvest month. White color indicates pixels with less than 0.001% maize cultivated area according to MIRCA2000.

7

Section F: Global maps of computed harvest dates for all crops (SAGE sowing dates prescribed)

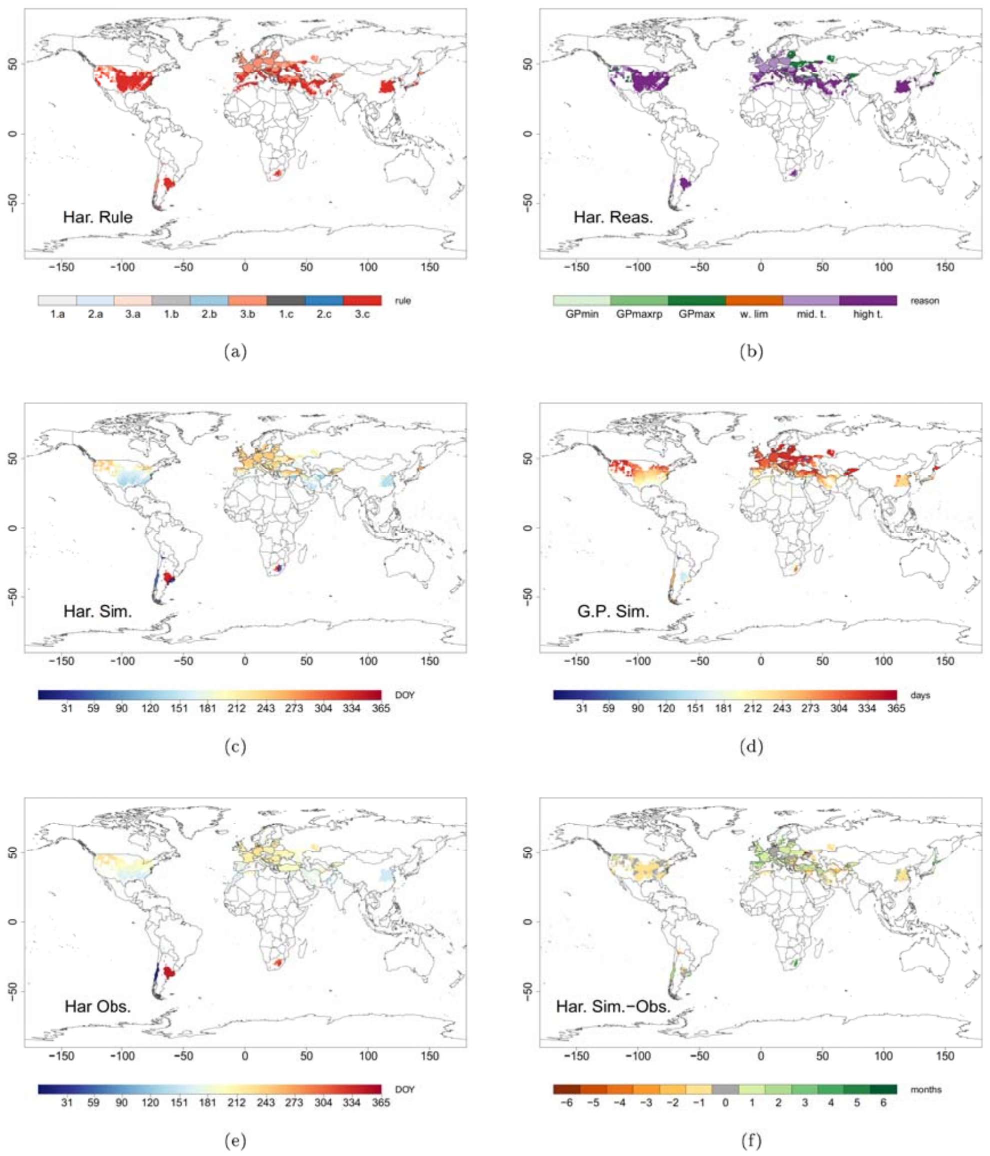


Figure F7: Results of the modelling workflow phases and evaluation for winter-wheat (a) agro-climatic zones of cultivation and corresponding rule applied for computing the harvest date (1.a-3.c); (b) realized harvest reason, representing the factor causing the end of the growing period (GP_{min} is earliest-maturing cultivar; GP_{maxrp} is longest grain-fill cultivar; GP_{max} is latest-maturing cultivar; $w.lim$ is water limitations; *mid t.* is mid-temperature limitations; *hight t.* is high-temperature limitations.); (c); computed harvest month with our modelling approach, where we have prescribed the sowing date from SAGE; (d) length of the computed total growing period (GP, sowing-to-harvest time); (e) observed harvest month from SAGE; (f) difference between computed and observed harvest month. White color indicates pixels for which SAGE has no reported data or pixels with less than 0.001% maize cultivated area according to MIRCA2000.

8

Section F: Global maps of computed harvest dates for all crops (SAGE sowing dates prescribed)

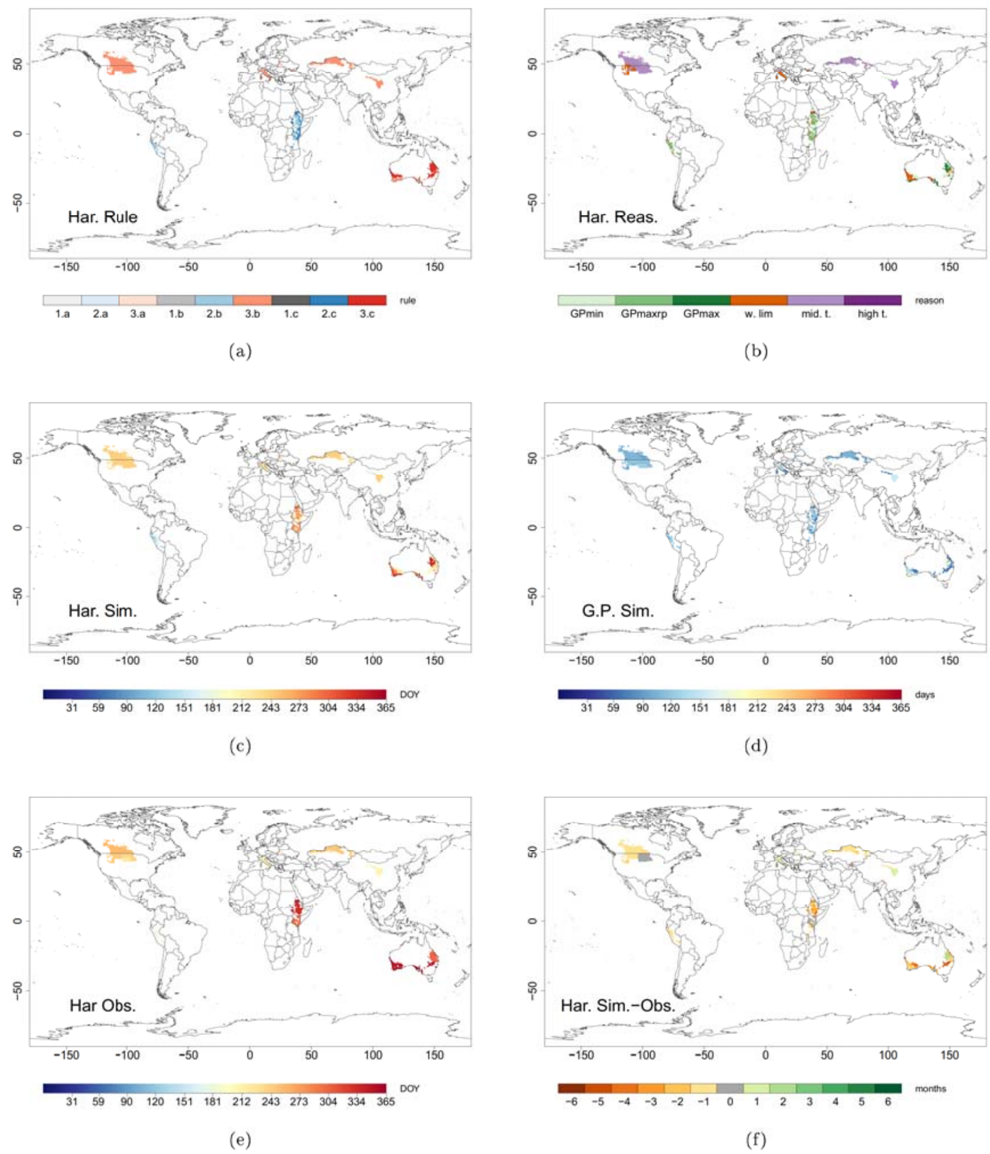


Figure F8: Results of the modelling workflow phases and evaluation for spring-wheat (a) agro-climatic zones of cultivation and corresponding rule applied for computing the harvest date (1.a-3.c); (b) realized harvest reason, representing the factor causing the end of the growing period (GP_{min} is earliest-maturing cultivar; GP_{maxrp} is longest grain-fill cultivar; GP_{max} is latest-maturing cultivar; $w.lim$ is water limitations; *mid t.* is mid-temperature limitations; *hight t.* is high-temperature limitations.); (c); computed harvest month with our modelling approach, where we have prescribed the sowing date from SAGE; (d) length of the computed total growing period (GP, sowing-to-harvest time); (e) observed harvest month from SAGE; (f) difference between computed and observed harvest month. White color indicates pixels for which SAGE has no reported data or pixels with less than 0.001% maize cultivated area according to MIRCA2000.

9

Section F: Global maps of computed harvest dates for all crops (SAGE sowing dates prescribed)

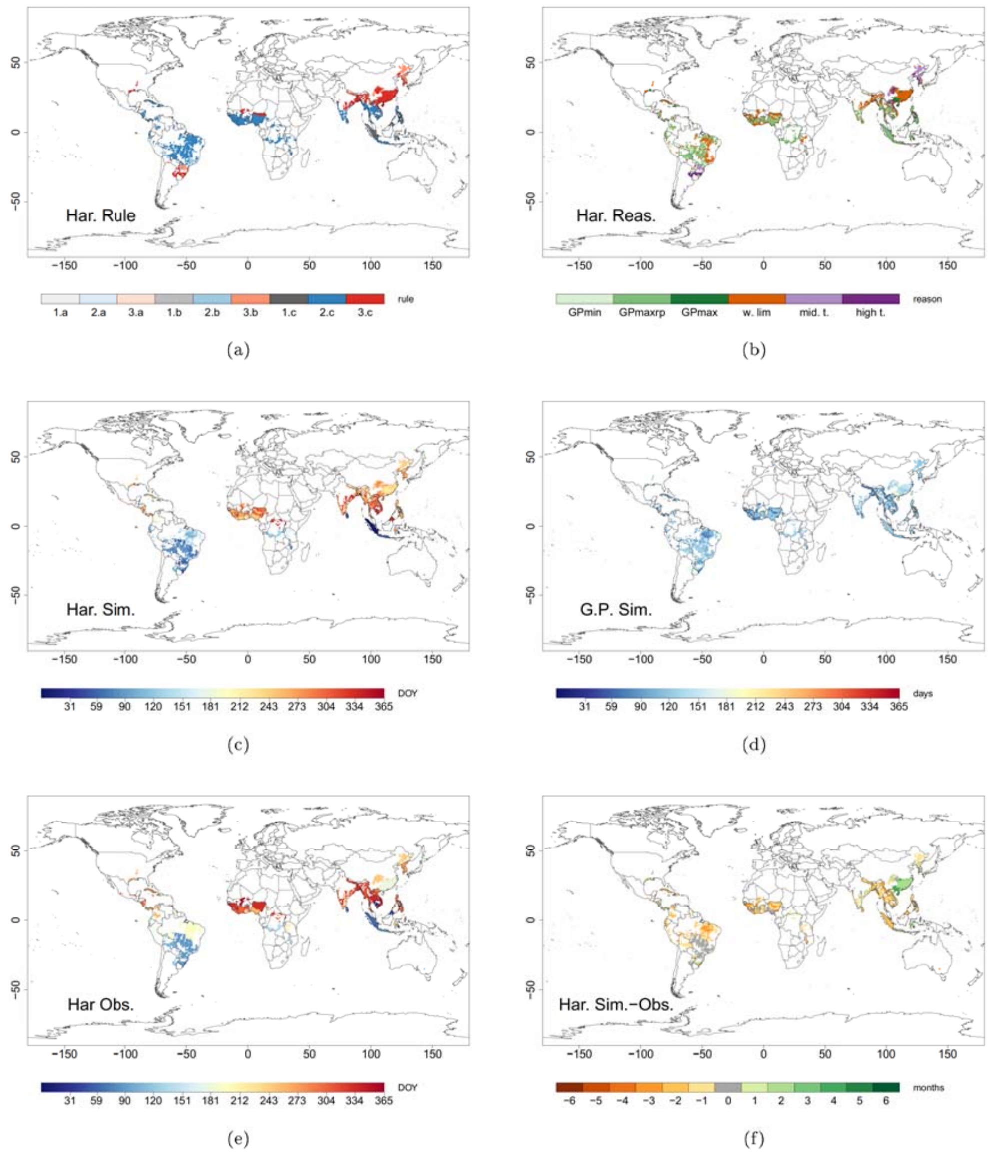


Figure F9: Results of the modelling workflow phases and evaluation for rice (a) agro-climatic zones of cultivation and corresponding rule applied for computing the harvest date (1.a-3.c); (b) realized harvest reason, representing the factor causing the end of the growing period (GP_{min} is earliest-maturing cultivar; GP_{maxrp} is longest grain-fill cultivar; GP_{max} is latest-maturing cultivar; $w.lim$ is water limitations; *mid t.* is mid-temperature limitations; *hight t.* is high-temperature limitations.); (c); computed harvest month with our modelling approach, where we have prescribed the sowing date from SAGE; (d) length of the computed total growing period (GP, sowing-to-harvest time); (e) observed harvest month from SAGE; (f) difference between computed and observed harvest month. White color indicates pixels for which SAGE has no reported data or pixels with less than 0.001% maize cultivated area according to MIRCA2000.

Section F: Global maps of computed harvest dates for all crops (SAGE sowing dates prescribed)

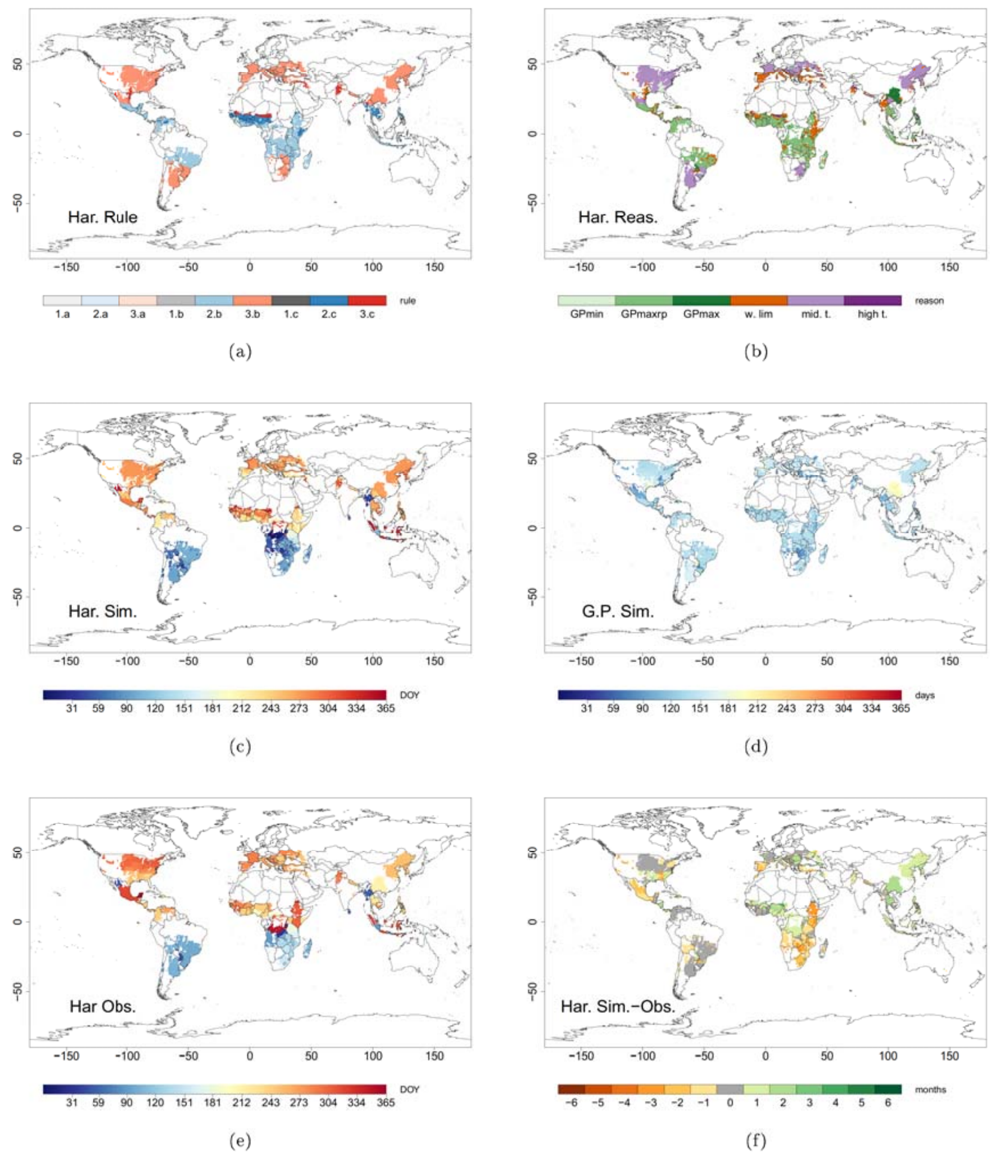


Figure F10: Results of the modelling workflow phases and evaluation for maize (a) agro-climatic zones of cultivation and corresponding rule applied for computing the harvest date (1.a-3.c); (b) realized harvest reason, representing the factor causing the end of the growing period (GP_{min} is earliest-maturing cultivar; GP_{maxrp} is longest grain-fill cultivar; GP_{max} is latest-maturing cultivar; $w.lim$ is water limitations; $mid\ t.$ is mid-temperature limitations; $hight\ t.$ is high-temperature limitations.); (c); computed harvest month with our modelling approach, where we have prescribed the sowing date from SAGE; (d) length of the computed total growing period (GP, sowing-to-harvest time); (e) observed harvest month from SAGE; (f) difference between computed and observed harvest month. White color indicates pixels for which SAGE has no reported data or pixels with less than 0.001% maize cultivated area according to MIRCA2000.

11

Section F: Global maps of computed harvest dates for all crops (SAGE sowing dates prescribed)

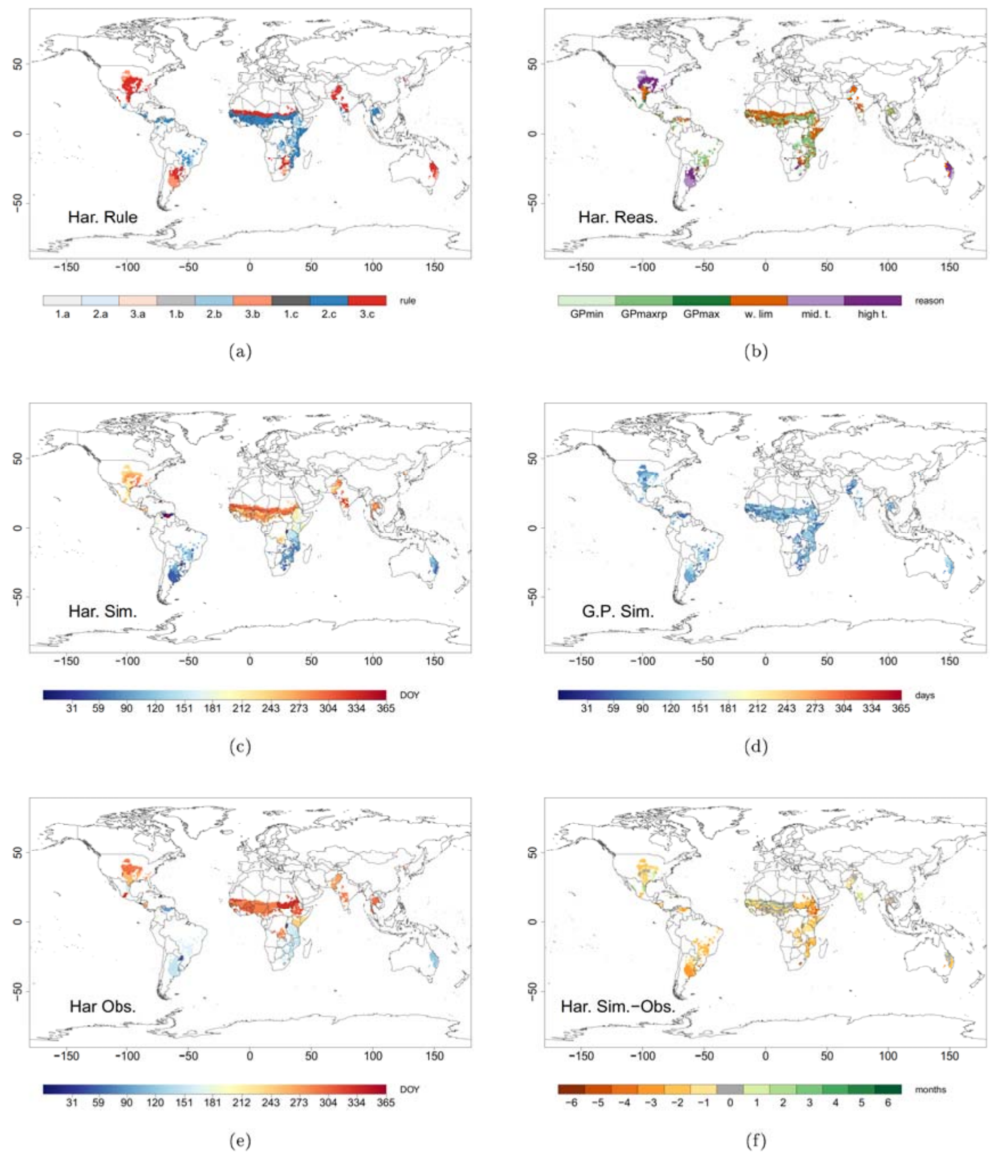


Figure F11: Results of the modelling workflow phases and evaluation for sorghum (a) agro-climatic zones of cultivation and corresponding rule applied for computing the harvest date (1.a-3.c); (b) realized harvest reason, representing the factor causing the end of the growing period (GP_{min} is earliest-maturing cultivar; GP_{maxrp} is longest grain-fill cultivar; GP_{max} is latest-maturing cultivar; *w.lim* is water limitations; *mid t.* is mid-temperature limitations; *hight t.* is high-temperature limitations.); (c); computed harvest month with our modelling approach, where we have prescribed the sowing date from SAGE; (d) length of the computed total growing period (GP, sowing-to-harvest time); (e) observed harvest month from SAGE; (f) difference between computed and observed harvest month. White color indicates pixels for which SAGE has no reported data or pixels with less than 0.001% maize cultivated area according to MIRCA2000.

12

Section F: Global maps of computed harvest dates for all crops (SAGE sowing dates prescribed)

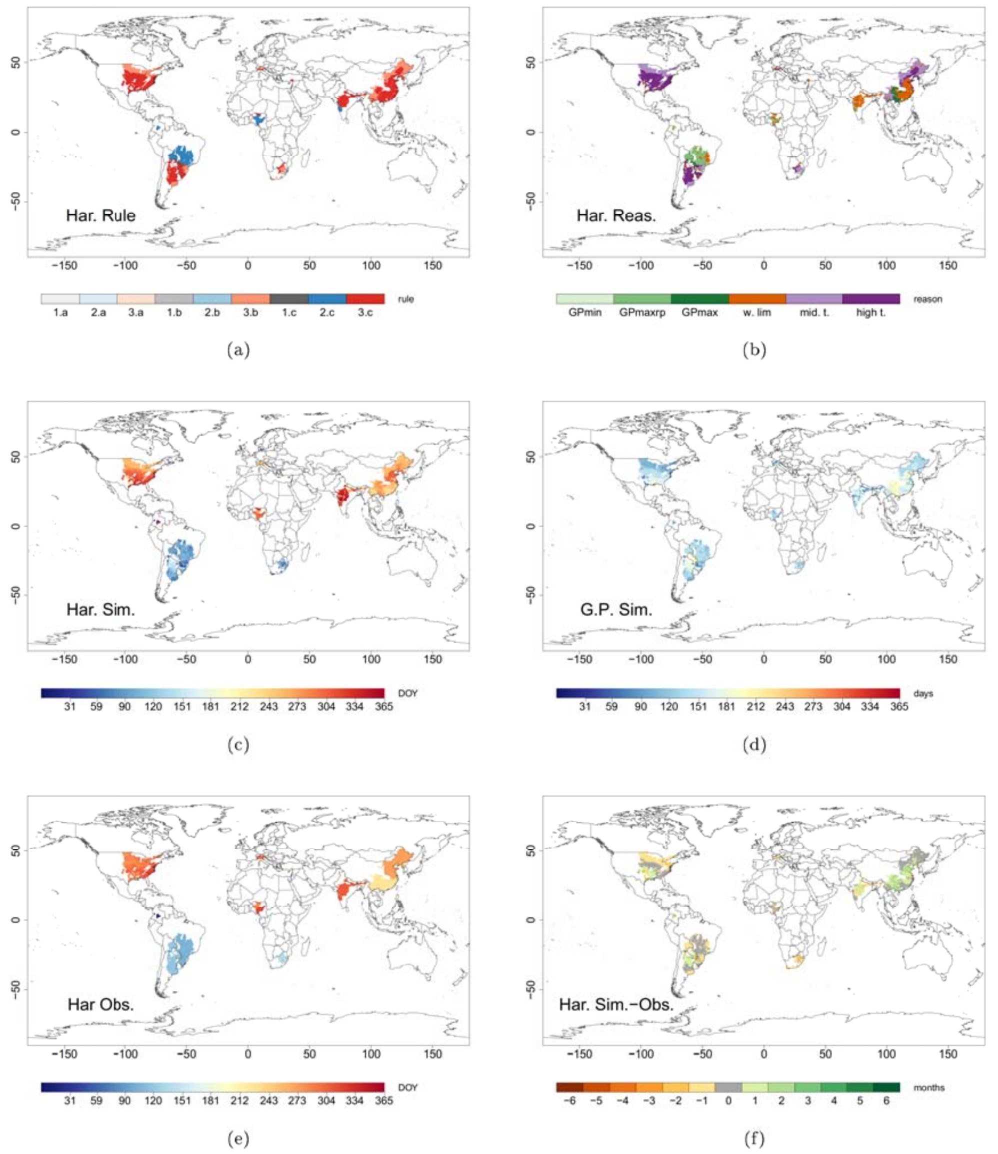


Figure F12: Results of the modelling workflow phases and evaluation for soybean (a) agro-climatic zones of cultivation and corresponding rule applied for computing the harvest date (1.a-3.c); (b) realized harvest reason, representing the factor causing the end of the growing period (GP_{min} is earliest-maturing cultivar; GP_{maxrp} is longest grain-fill cultivar; GP_{max} is latest-maturing cultivar; $w.lim$ is water limitations; $mid\ t.$ is mid-temperature limitations; $hight\ t.$ is high-temperature limitations.); (c); computed harvest month with our modelling approach, where we have prescribed the sowing date from SAGE; (d) length of the computed total growing period (GP, sowing-to-harvest time); (e) observed harvest month from SAGE; (f) difference between computed and observed harvest month. White color indicates pixels for which SAGE has no reported data or pixels with less than 0.001% maize cultivated area according to MIRCA2000.

13

Section G: Global maps of computed sowing dates, harvest dates and growing period lengths for all crops

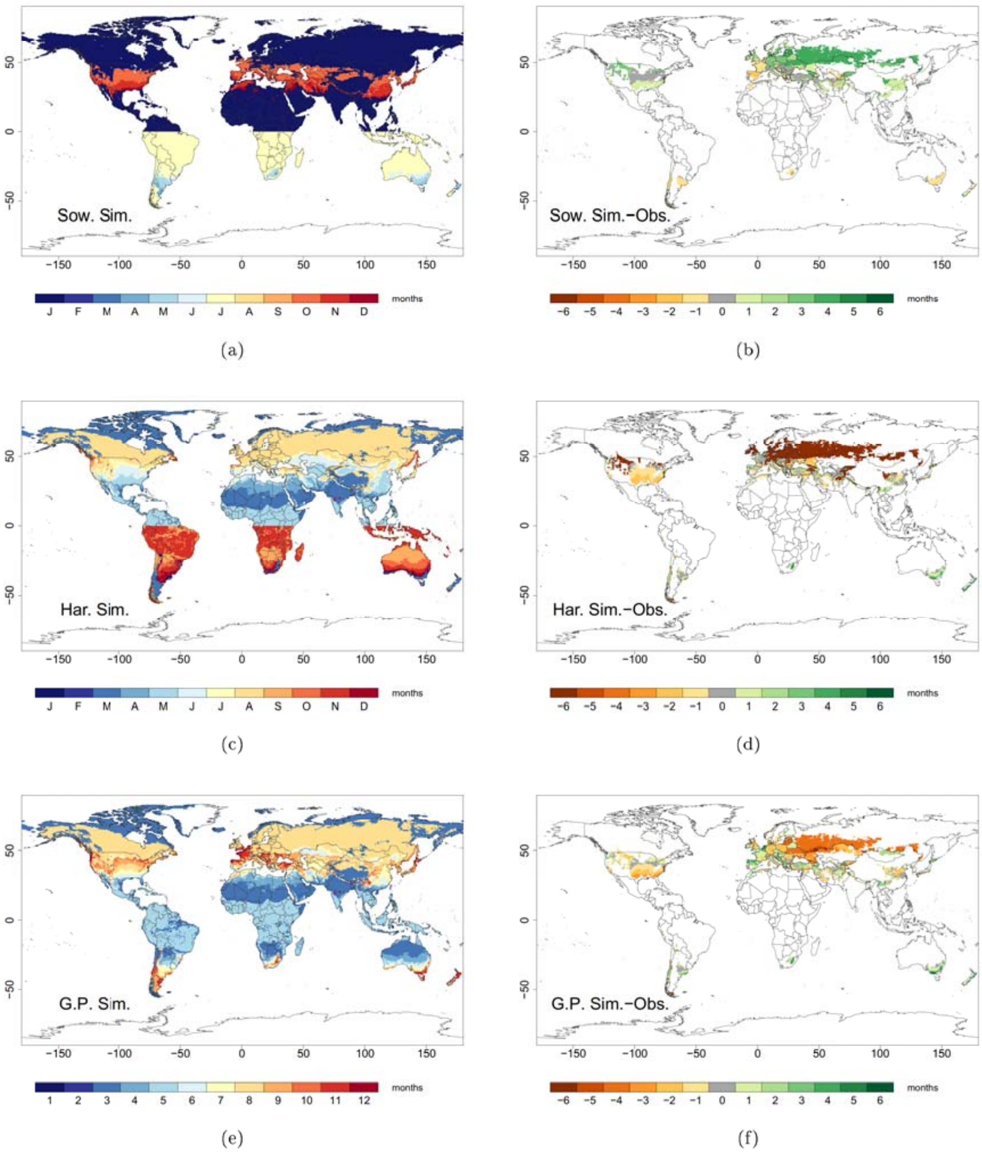


Figure G1: winter-wheatSimulated months of (a) sowing, (c) harvest, (e) total growing period; difference between simulated and observed (MIRCA2000) months of (b) sowing, (d) harvest, (f) total growing period. Simulated values are displayed for all grid-cells where climate data are available. Dark-blue colors (1-3 months) in (e) indicate short GPs due to unsuitable or very much constraining growing seasons; white color in (a), (c), (e) indicates missing climate data; white color in (b), (d), (f) indicates pixels with less than 0.001% maize cultivated area.

Section G: Global maps of computed sowing dates, harvest dates and growing period lengths for all crops

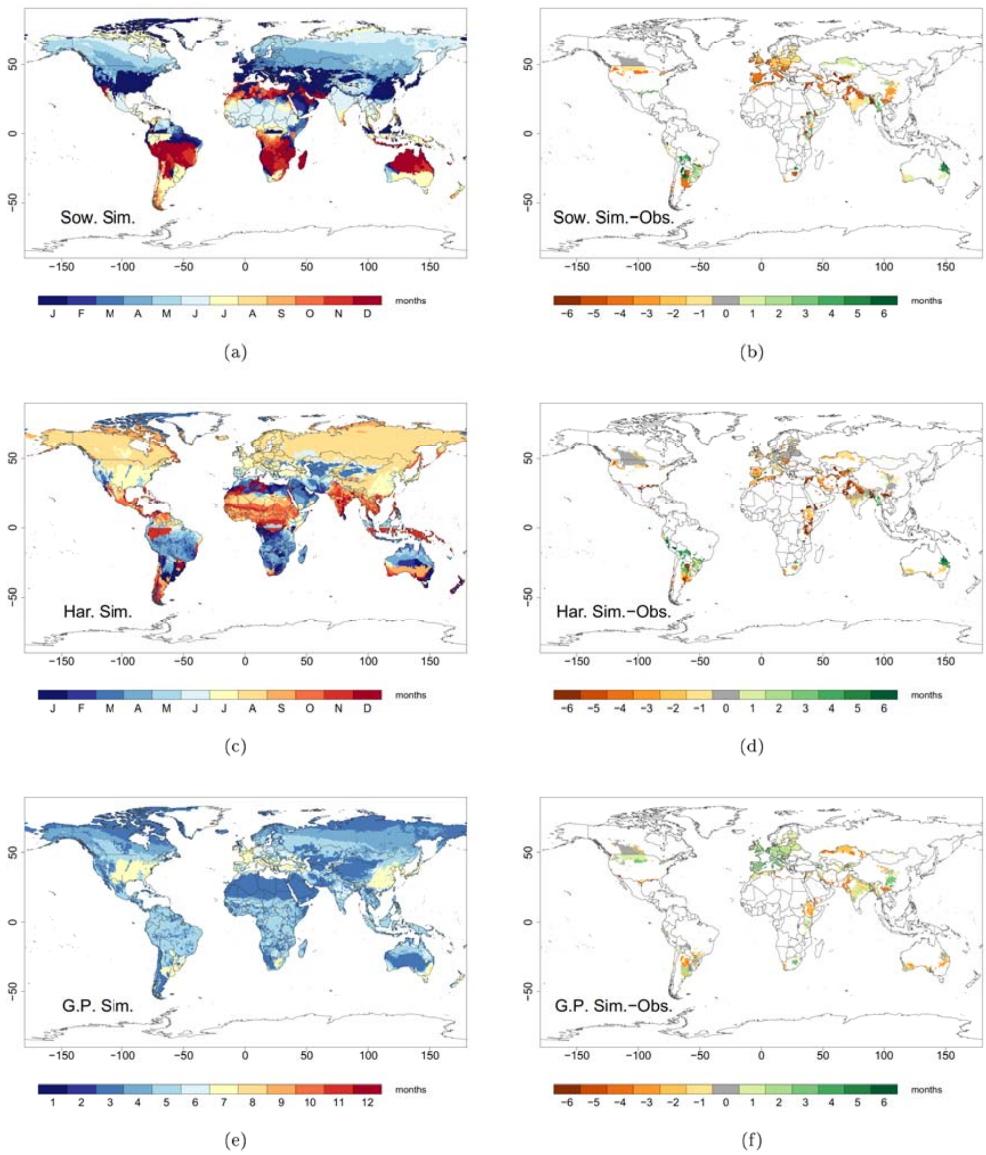


Figure G2: spring-wheatSimulated months of (a) sowing, (c) harvest, (e) total growing period; difference between simulated and observed (MIRCA2000) months of (b) sowing, (d) harvest, (f) total growing period. Simulated values are displayed for all grid-cells where climate data are available. Dark-blue colors (1-3 months) in (e) indicate short GPs due to unsuitable or very much constraining growing seasons; white color in (a), (c), (e) indicates missing climate data; white color in (b), (d), (f) indicates pixels with less than 0.001% maize cultivated area.

3

Section G: Global maps of computed sowing dates, harvest dates and growing period lengths for all crops

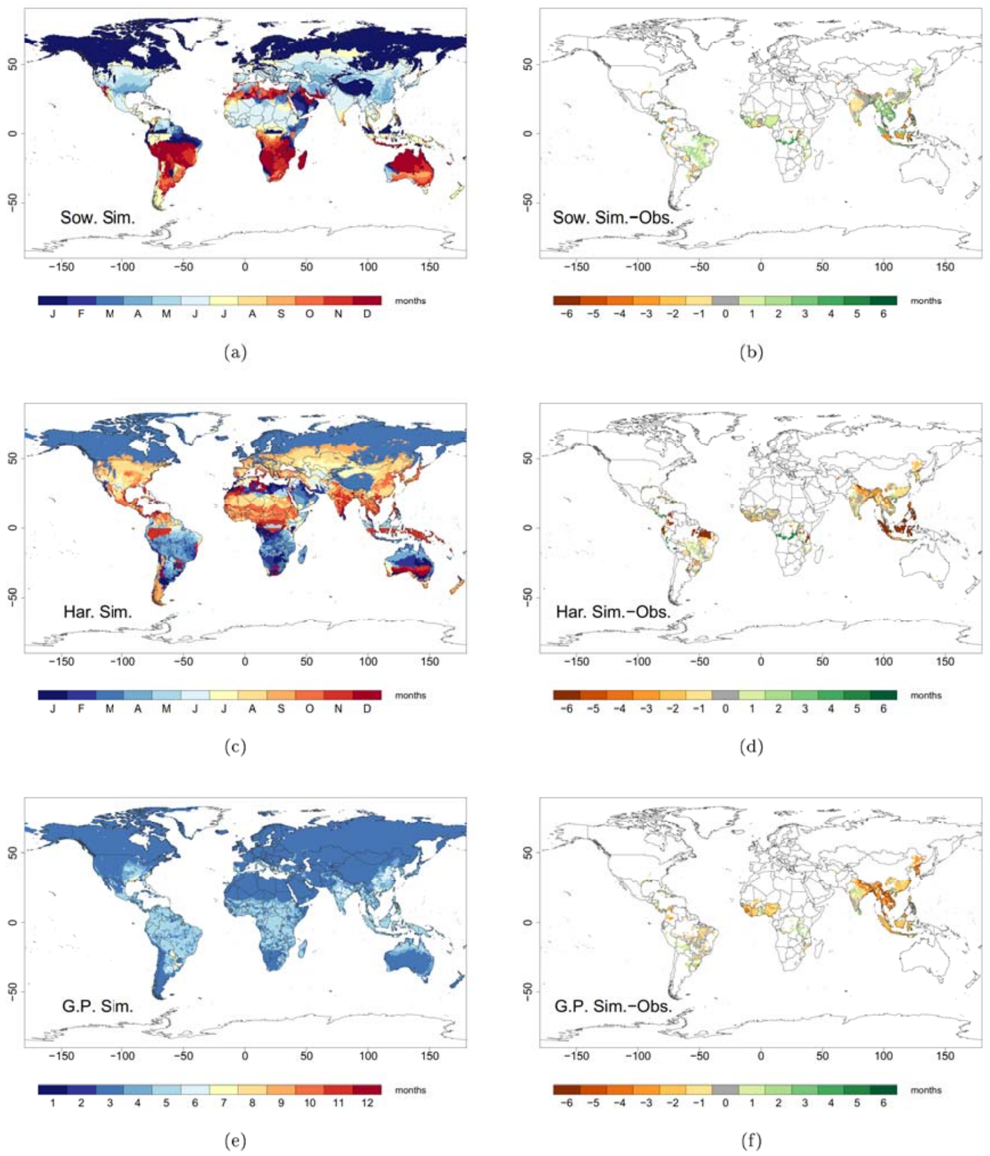


Figure G3: riceSimulated months of (a) sowing, (c) harvest, (e) total growing period; difference between simulated and observed (MIRCA2000) months of (b) sowing, (d) harvest, (f) total growing period. Simulated values are displayed for all grid-cells where climate data are available. Dark-blue colors (1-3 months) in (e) indicate short GPs due to unsuitable or very much constraining growing seasons; white color in (a), (c), (e) indicates missing climate data; white color in (b), (d), (f) indicates pixels with less than 0.001% maize cultivated area.

Section G: Global maps of computed sowing dates, harvest dates and growing period lengths for all crops

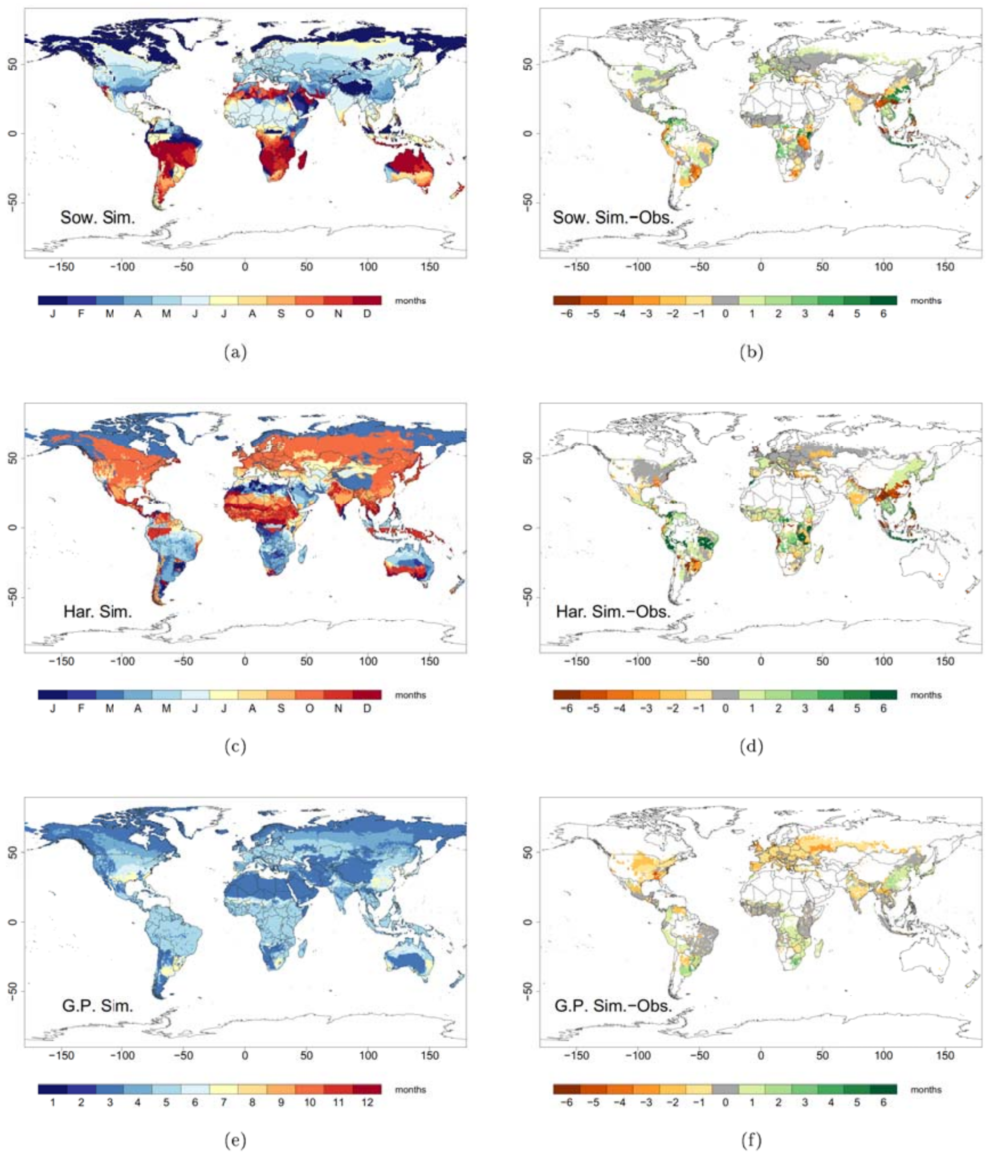


Figure G4: maizeSimulated months of (a) sowing, (c) harvest, (e) total growing period; difference between simulated and observed (MIRCA2000) months of (b) sowing, (d) harvest, (f) total growing period. Simulated values are displayed for all grid-cells where climate data are available. Dark-blue colors (1-3 months) in (e) indicate short GPs due to unsuitable or very much constraining growing seasons; white color in (a), (c), (e) indicates missing climate data; white color in (b), (d), (f) indicates pixels with less than 0.001% maize cultivated area.

Section G: Global maps of computed sowing dates, harvest dates and growing period lengths for all crops

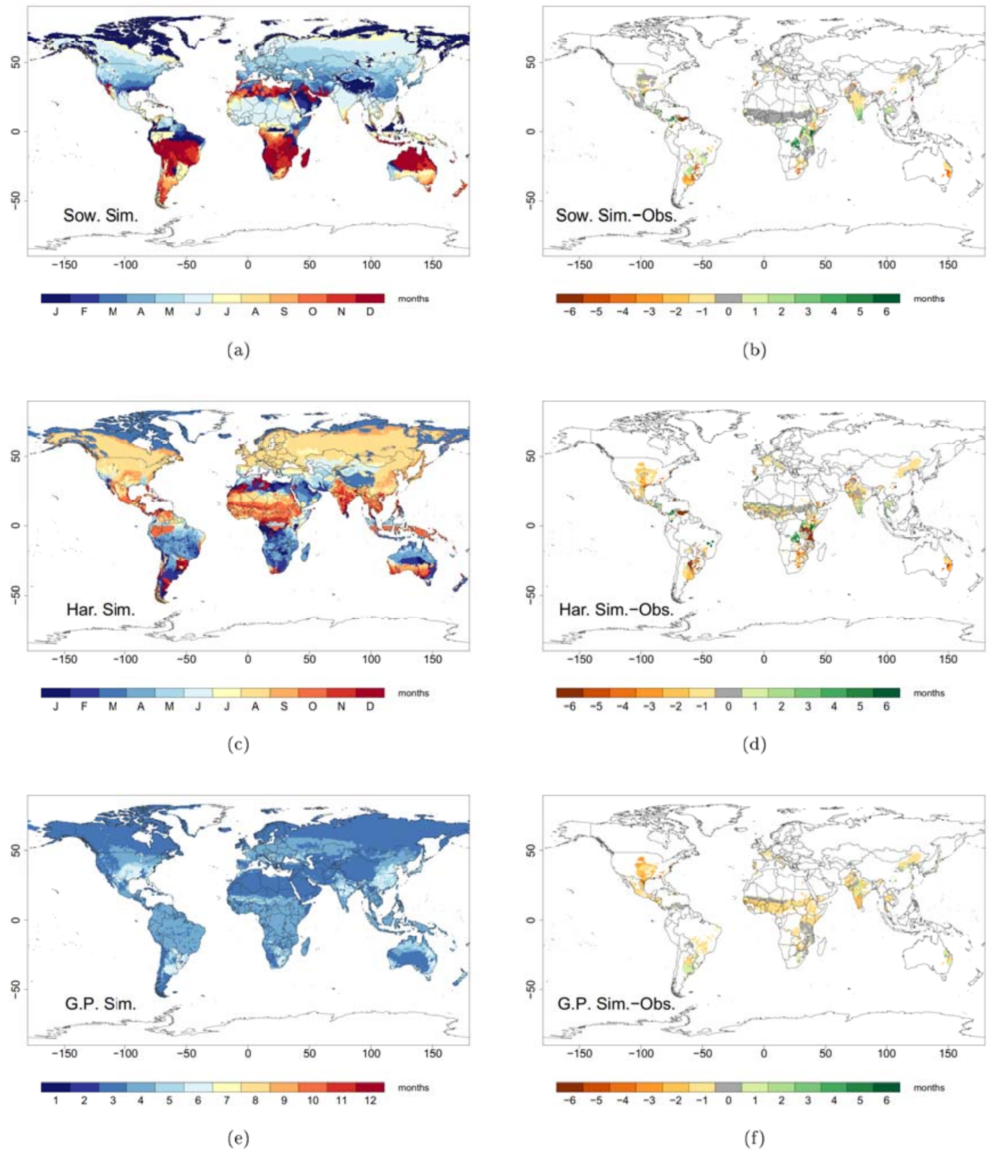


Figure G5: sorghumSimulated months of (a) sowing, (c) harvest, (e) total growing period; difference between simulated and observed (MIRCA2000) months of (b) sowing, (d) harvest, (f) total growing period. Simulated values are displayed for all grid-cells where climate data are available. Dark-blue colors (1-3 months) in (e) indicate short GPs due to unsuitable or very much constraining growing seasons; white color in (a), (c), (e) indicates missing climate data; white color in (b), (d), (f) indicates pixels with less than 0.001% maize cultivated area.

Section G: Global maps of computed sowing dates, harvest dates and growing period lengths for all crops

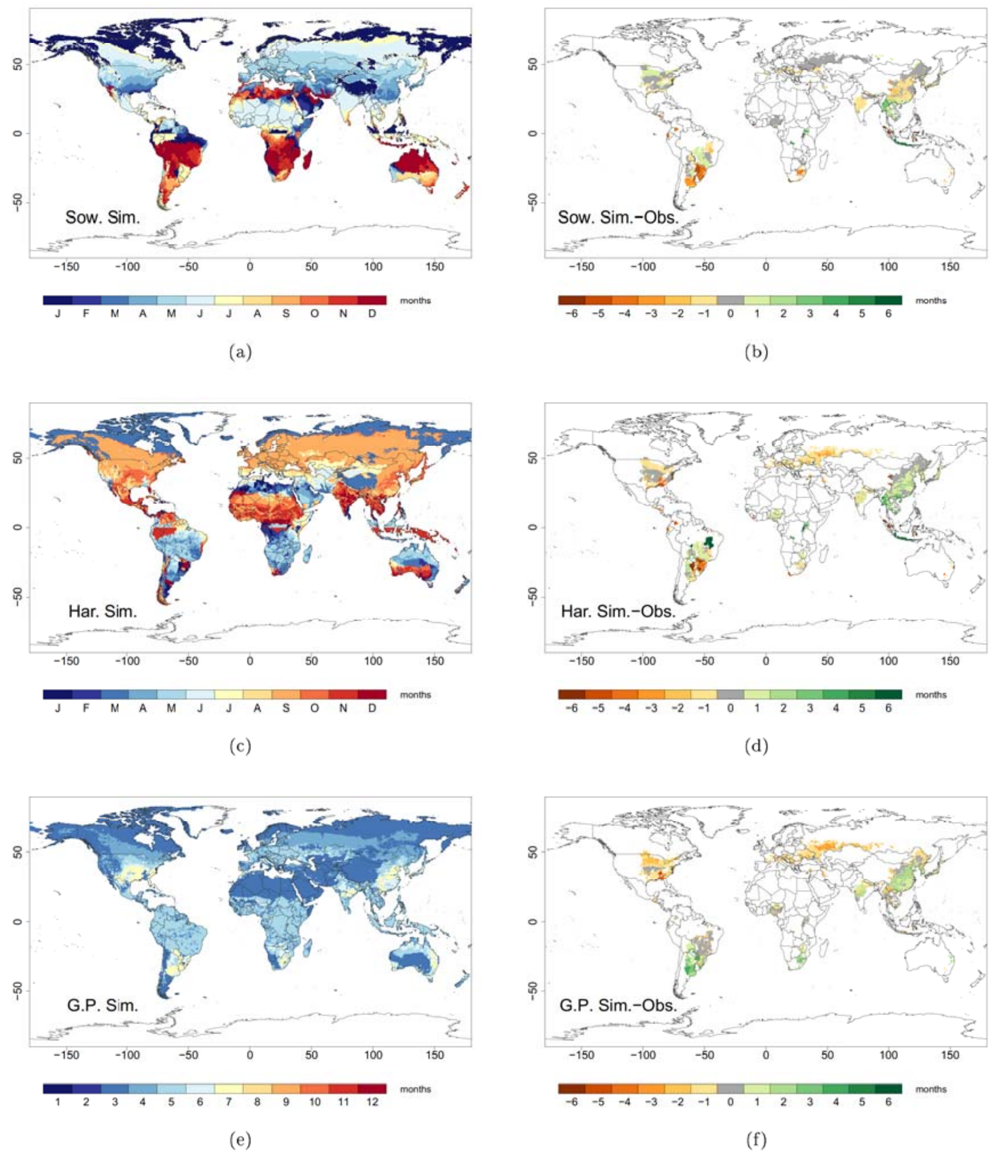


Figure G6: soybeanSimulated months of (a) sowing, (c) harvest, (e) total growing period; difference between simulated and observed (MIRCA2000) months of (b) sowing, (d) harvest, (f) total growing period. Simulated values are displayed for all grid-cells where climate data are available. Dark-blue colors (1-3 months) in (e) indicate short GPs due to unsuitable or very much constraining growing seasons; white color in (a), (c), (e) indicates missing climate data; white color in (b), (d), (f) indicates pixels with less than 0.001% maize cultivated area.

7

C

Supplementary Information for Chapter 4

Global crop yields benefit from adapting phenology to future climate change

1 Supplementary text S1

1.1 LPJmL model description

To simulate phenology and yields of five crops (maize, rice, sorghum, soybean and wheat) we used the LPJmL (Lund-Potsdam-Jena managed Land) Dynamic Global Vegetation Model, which is briefly described here below. Details of the model functions can be found in (Bondeau et al., 2007; Schaphoff et al., 2018; Jägermeyr et al., 2018).In LPJmL crop phenological development and growth are simulated at a daily time step. The crop annual cycle is represented by one unique phenological phase from emergence (assumed equal to sowing) to maturity (assumed equal to harvest). Phenological development is simulated based on the thermal-time model, including the effect of both vernalization and photoperiod. Sowing dates and thermal unit requirements (TUs) are prescribed based on the external rule-based algorithm (refer to the Methods section). From the day of sowing, effective TUs for phenological development are accumulated. Daily effective TUs are computed as the difference between the mean air temperature on that day and the crop-specific base temperature for phenological development. For wheat only, if sowing occurs in autumn (DOY 243-356 in the Northern Hemisphere; DOY 59-181 in the Southern Hemisphere) we assume cultivars sensitive to vernalization. The maximum vernalization requirements are set 70 days. The vernalization effectiveness is measured daily by a scaling factor (0-1), which is then multiplied to the daily TUs. The scaling factor is computed by a linear response function with a range of optimal temperatures. Temperature for effective vernalization range between -4°C and +17°C, with an optimum range between 3°C and 10°C. In this study all crops are assumed to be insensitive to photoperiod (Psens set to 1). Crop biomass growth is simulated by daily Carbon accumulation and allocation to different plan organs (roots, leaves, storage organs, mobile reserves and stem). The fraction of Carbon allocated to each pool is a function of the fraction of completed phenological progess. Water stess increases allocation to the roots and reduces allocation to the leaves. The daily Net Primary Production (NPP) it the result of the Gross Primary Production (daily gross photosynthesis) reduced by the respiration costs. Gross photosynthesis is simulated as a function of absorbed photosynthetically active radiation, CO_2 atmospheric mixing ratio, air temperature, daylength and canopy conductance. Photosynthesys rate is given by the minimum between light-limited and rubisco-limited photosynthesis rates, with distinguished pathways for C_3 and C_4 crops. Respiration is tissue specific and it is also driven by temperature. If daily NPP is limiting, allocation follows a hierarchical order from roots, to leaves, to storage organs, therefore penalizing the harvest index. Simulations were run for each individual crop at 0.5 degree spatial resolution, for consecutive 20 years of two time periods: 1986-2005 and 2080-2099.

2 Supplementary tables

Table S1: Temperature thresholds used for computing the cropping calendars. Values are taken from Waha et al. (2012) and Minoli et al. (2019). Tbase sowing is the temperature threshold for sowing; Tbase yield formation is the base temperature for the crop reproductive development, below which the crop cannot complete the reproductive cycle; Topt yield formation is the optimum temperature for the crop reproductive grain formation; Tbase Thermal time is the base temperature for phenological development.

Crop	Tbase Sowing	Tbase Yield formation	Topt Yield formation	Tbase Thermal Time
Maize	14	7	30	5-15[1]
Rice	18	8	24	10
Sorghum	12	8	25	2
Soybean	13	6	23	10
Wheat (winter, spring type)	5, 12	1,1	21, 25	0

[1] depending on local mean annual temperature (Jägermeyr & Frieler 2018)

3 Suppementary figures

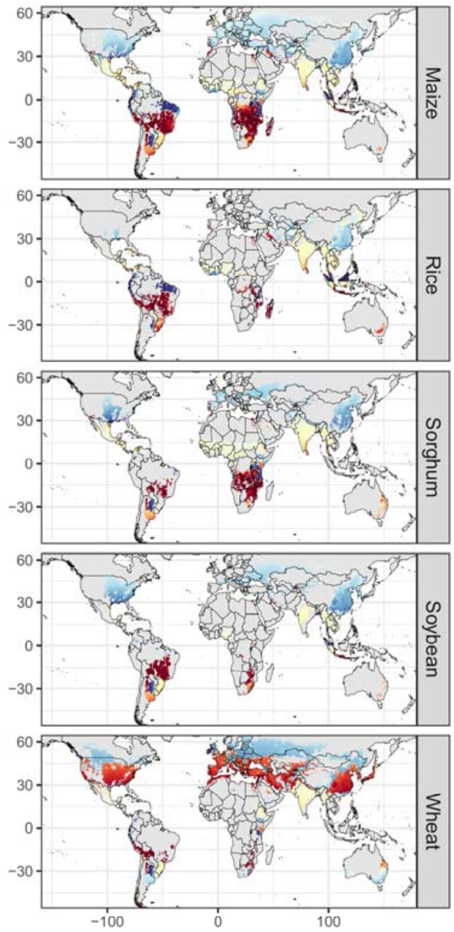


Figure S1: Computed sowing dates (day of the year) in the reference time period (1986-2005). Sowing dates are computed for the individual crops, with no difference between rainfed and irrigated crops.

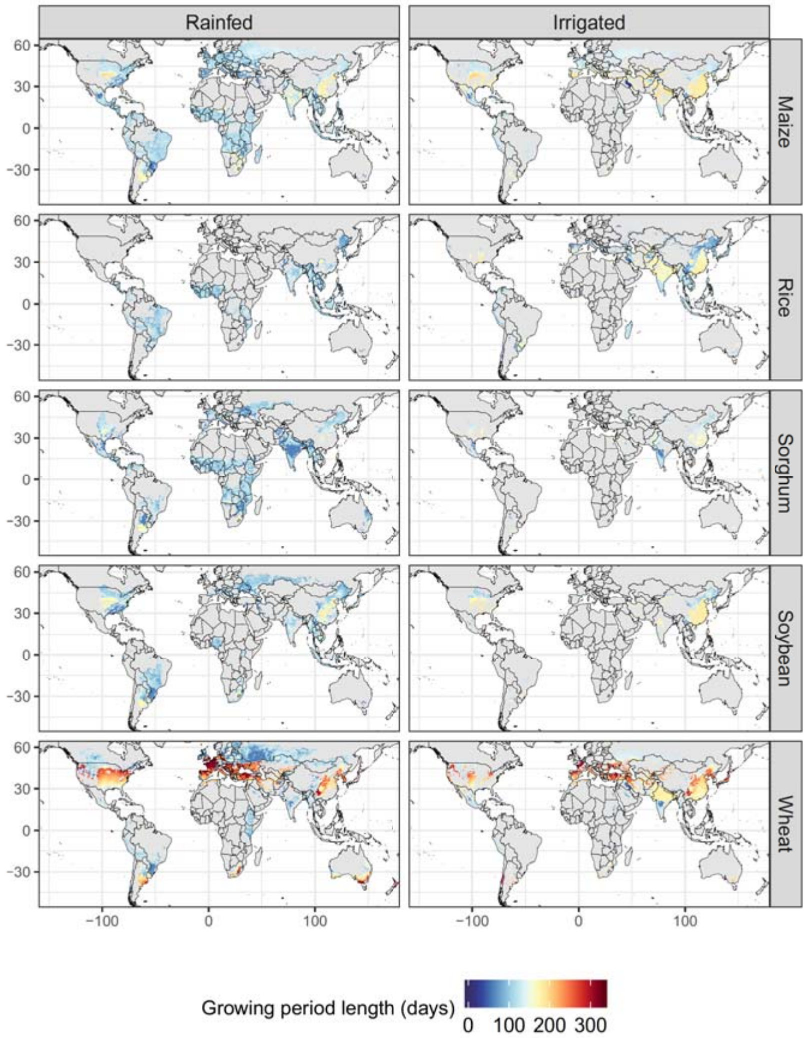


Figure S2: Computed growing period lengths (days) in the reference time period (1986-2005). Growing periods are computed for the individual crops, and irrigation setting. Growing period of rainfed crops are shorter in grid cells where the algorithm detects the occurrence of terminal water limitation (based on thresholds of Precipitation / Potential Evapotranspiration ratio).

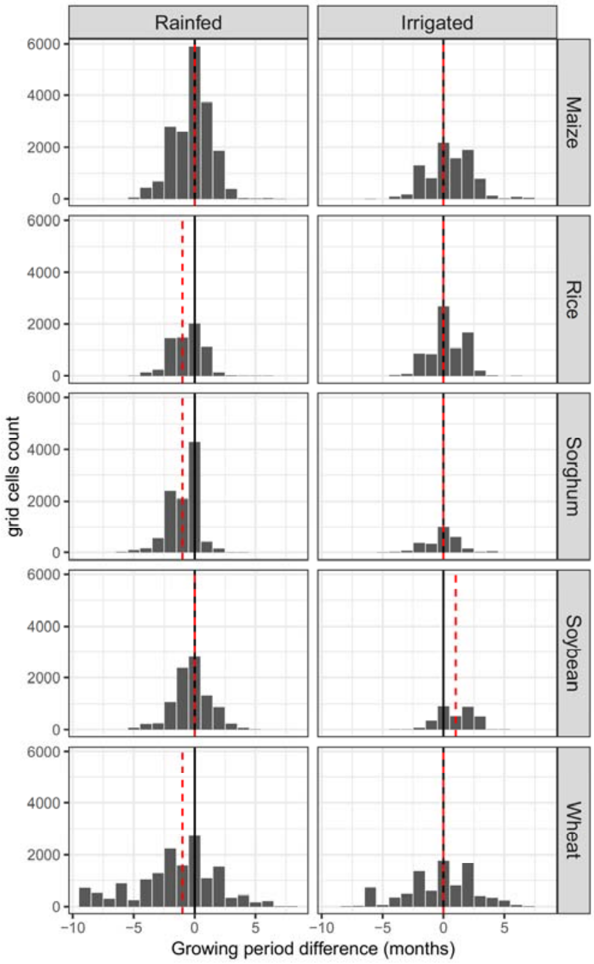


Figure S3: Comparison of simulated and reported growing periods. The histograms display the frequency distribution of the differences between computed (Waha et al., 2012; Minoli et al., 2019) and reported (Portmann et al., 2010) growing periods, for individual crops and irrigation system. To allow the comparison, a maturity to harvest (days) parameter was added to the computed growing period, and its unit was transformed from days to months. The black line is the zero line, the red-dashed line is the median of the differences across all grid cells and GCMs.

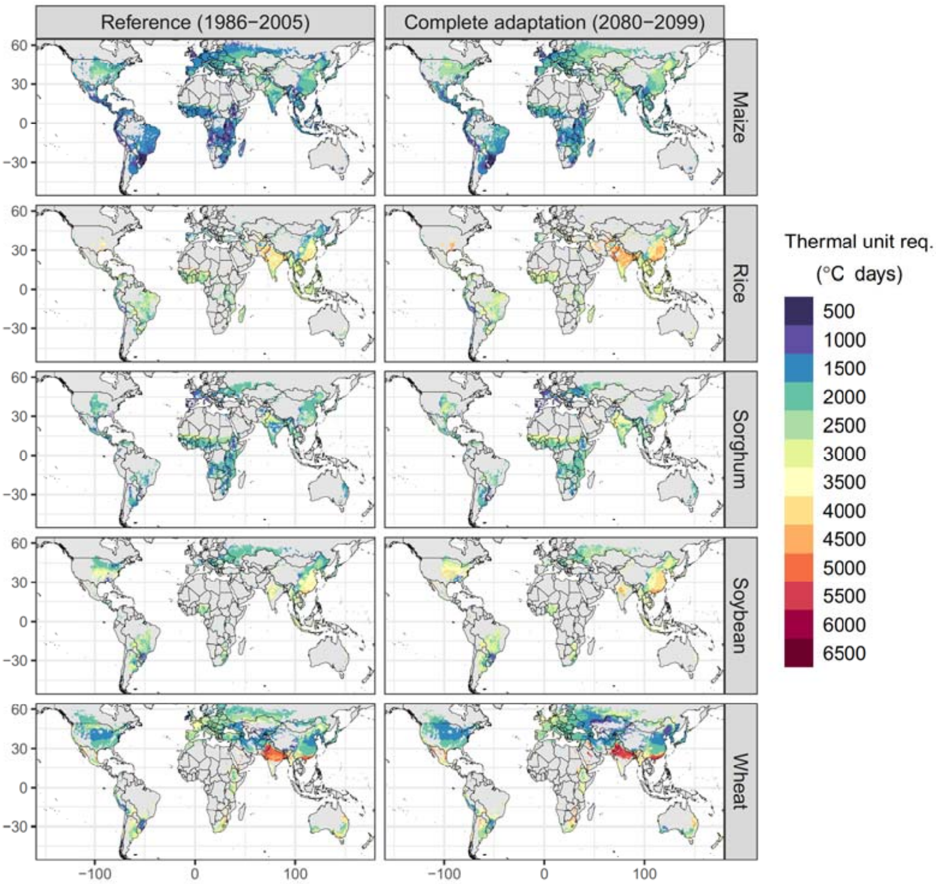


Figure S4: Current and future thermal unit requirements (TUs). Maps of cultivar classes, represented by the TUs, are shown under the reference and complete adaptation management assumptions. TUs are averaged across GCMs. In cells where both rainfed and irrigated area is reported, the maximum between rainfed and irrigated crops is shown . The colors indicate the upper limit of the interval starting from 0 TUs. Area that is not part of present cropland is depicted in gray.

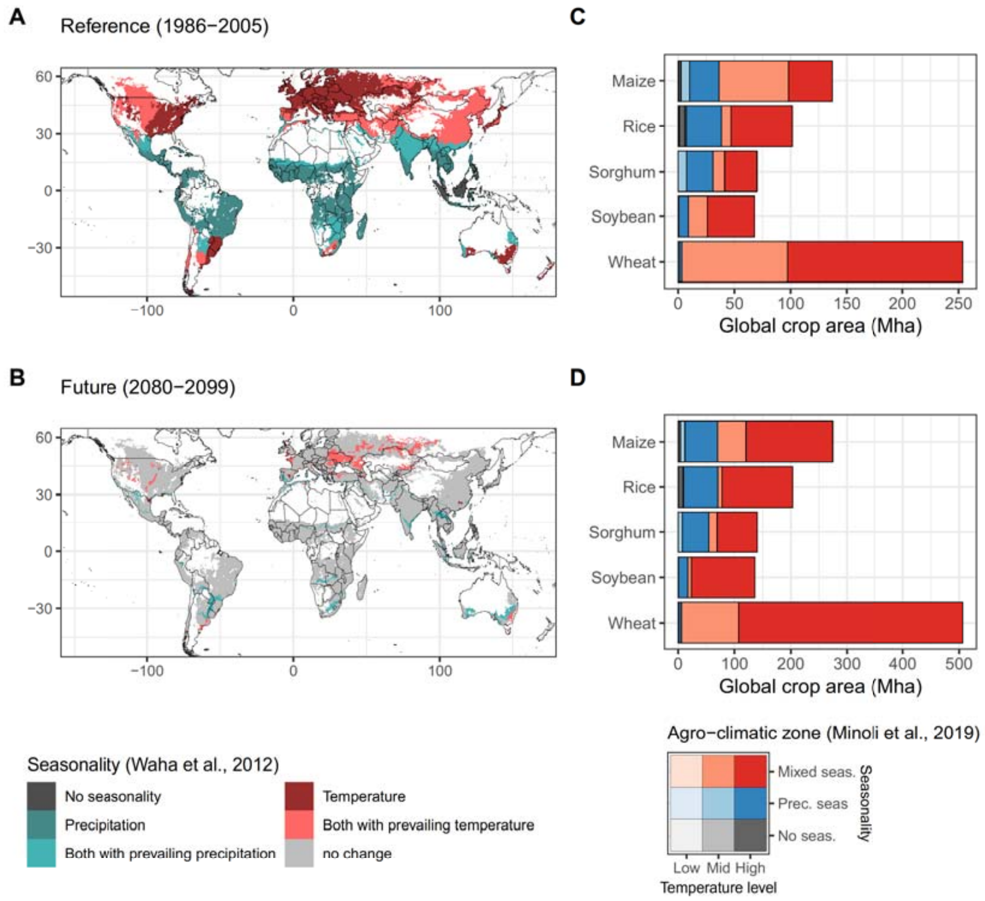


Figure S5: As Figure 3 but for GCM GFDL-ESM2M

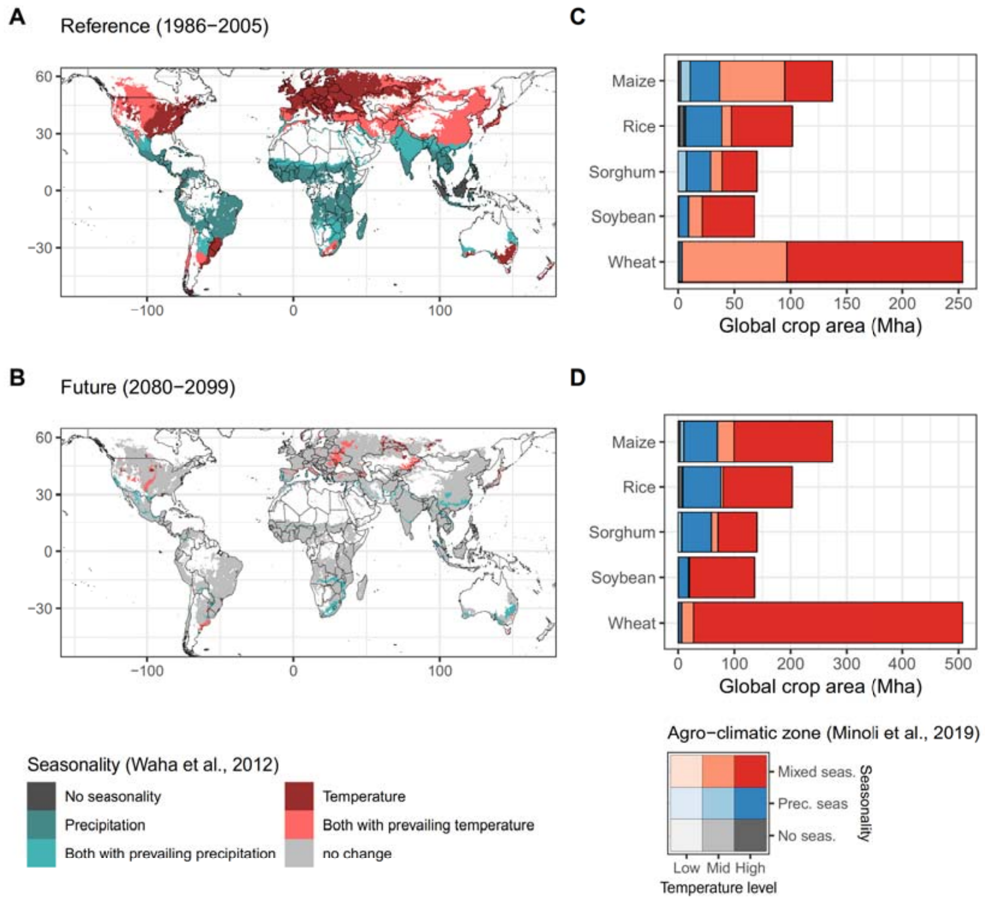


Figure S6: As Figure 3 but for GCM IPSL-CM5A-LR

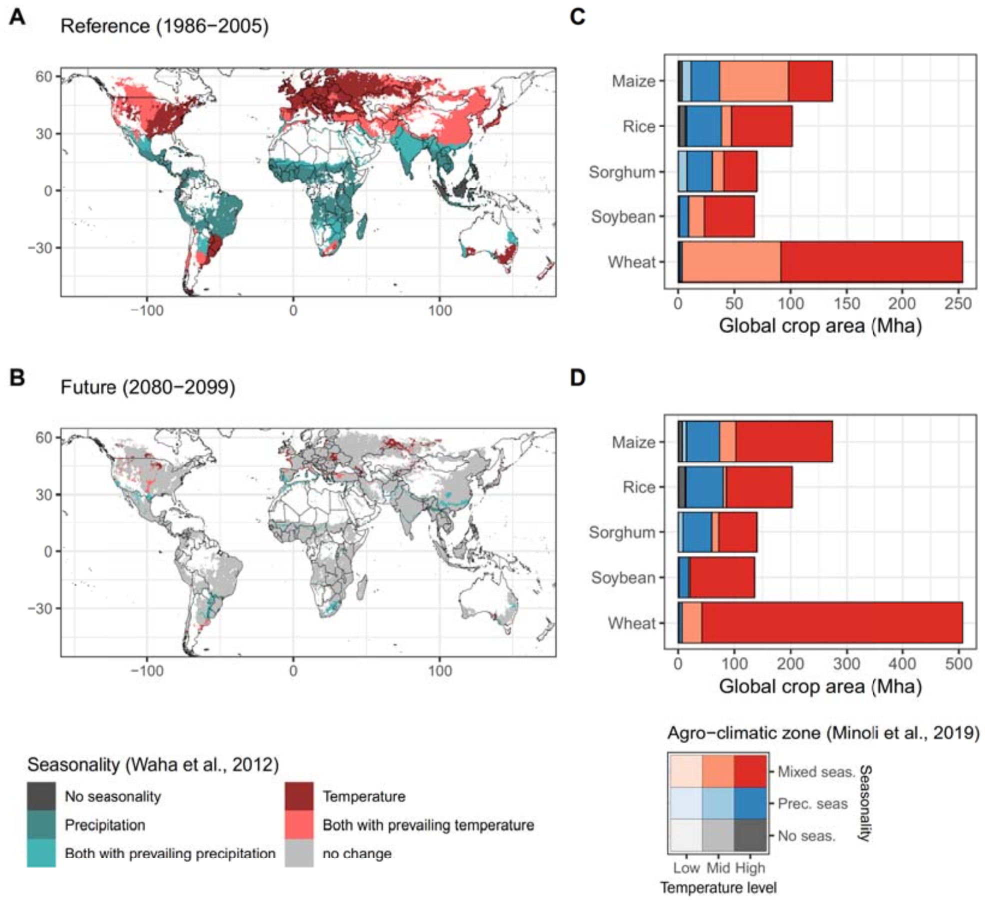


Figure S7: As Figure 3 but for GCM MIROC5

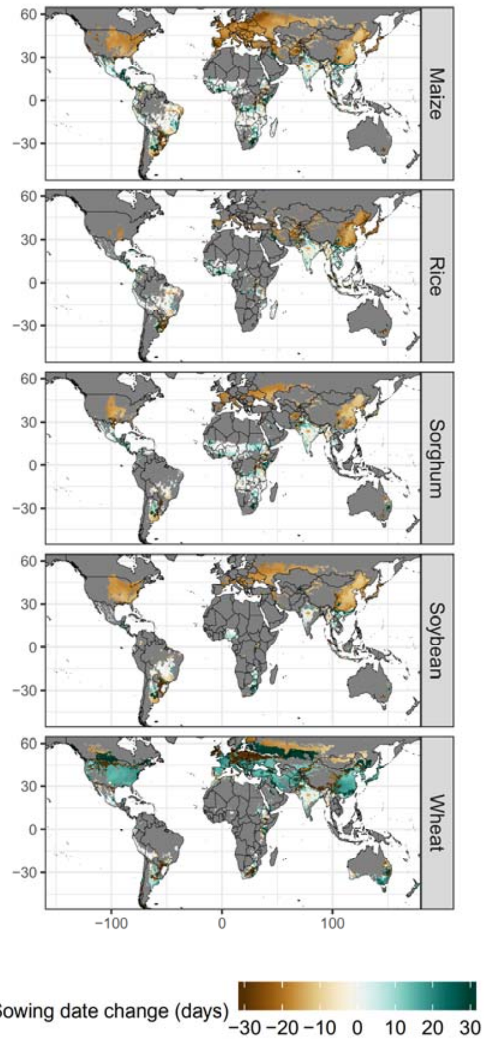


Figure S8: Global patterns of sowing date changes (days) between complete adaptation (2080-2099) and reference (1986-2005) scenarios. The legend scale is cut to the range -30 to +30 days to highlight smaller differences and allow comparison between different crops. Area that is not part of present cropland is depicted in gray.

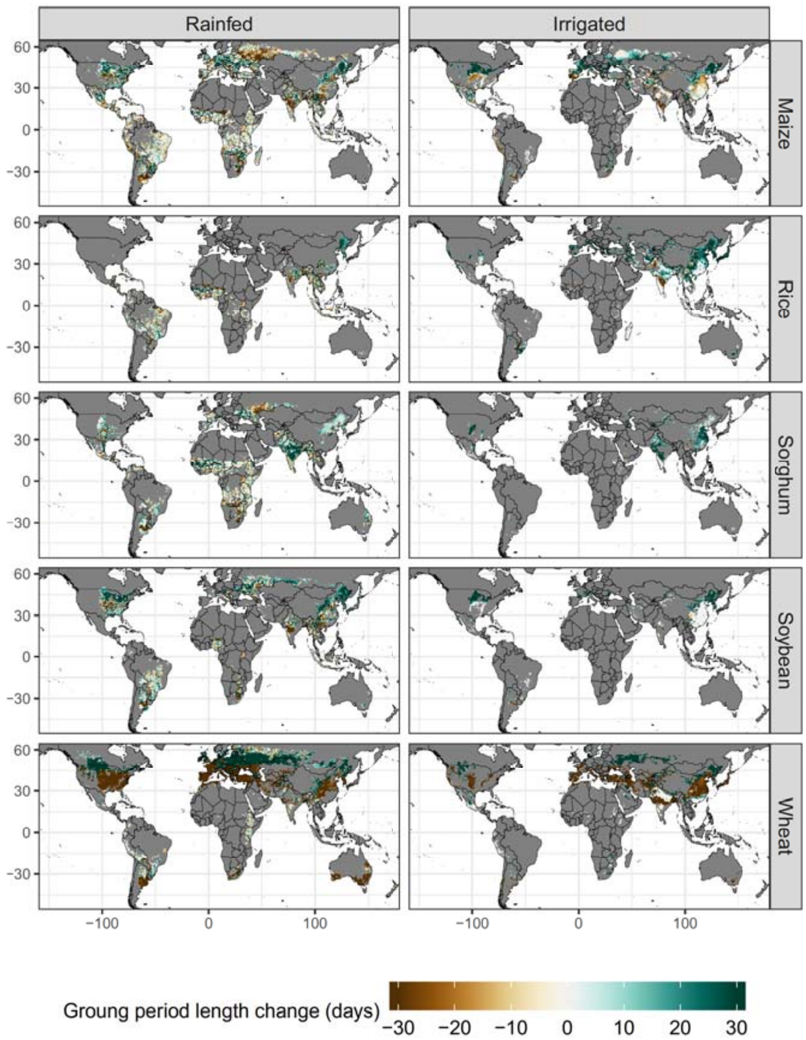


Figure S9: Global patterns of growing period length changes (days) between complete adaptation (2080-2099) and reference (1986-2005) scenarios. The legend scale is cut to the range -30 to +30 days to highlight smaller differences and allow comparison between different crops. Area that is not part of present cropland is depicted in gray.

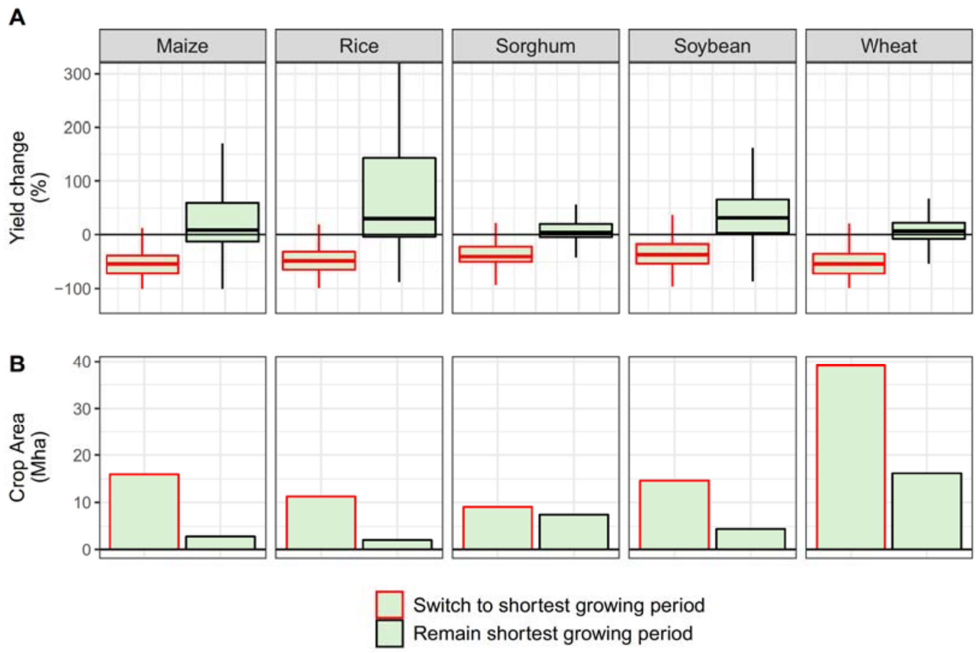


Figure S10: Effect and maladaptation of choosing the shortest growing period (GPmin) in areas unsuitable to crop growth. Only grid cells where the realized harvest reason under complete adaptation is the earliest-maturing cultivar are included in the box plots (Panel A) and the corresponding area to each box is displayed by the bar plots beneath (panel B). Grid cells are split between those (black) having GPmin in both reference and future scenarios, and those (red) that switch to GPmin in the future scenario only. Yield changes are computed as the relative difference between the future (2080-2099) and the reference time period (1986-2005). Boxes and whiskers in panel A are defined as in Figure 5.

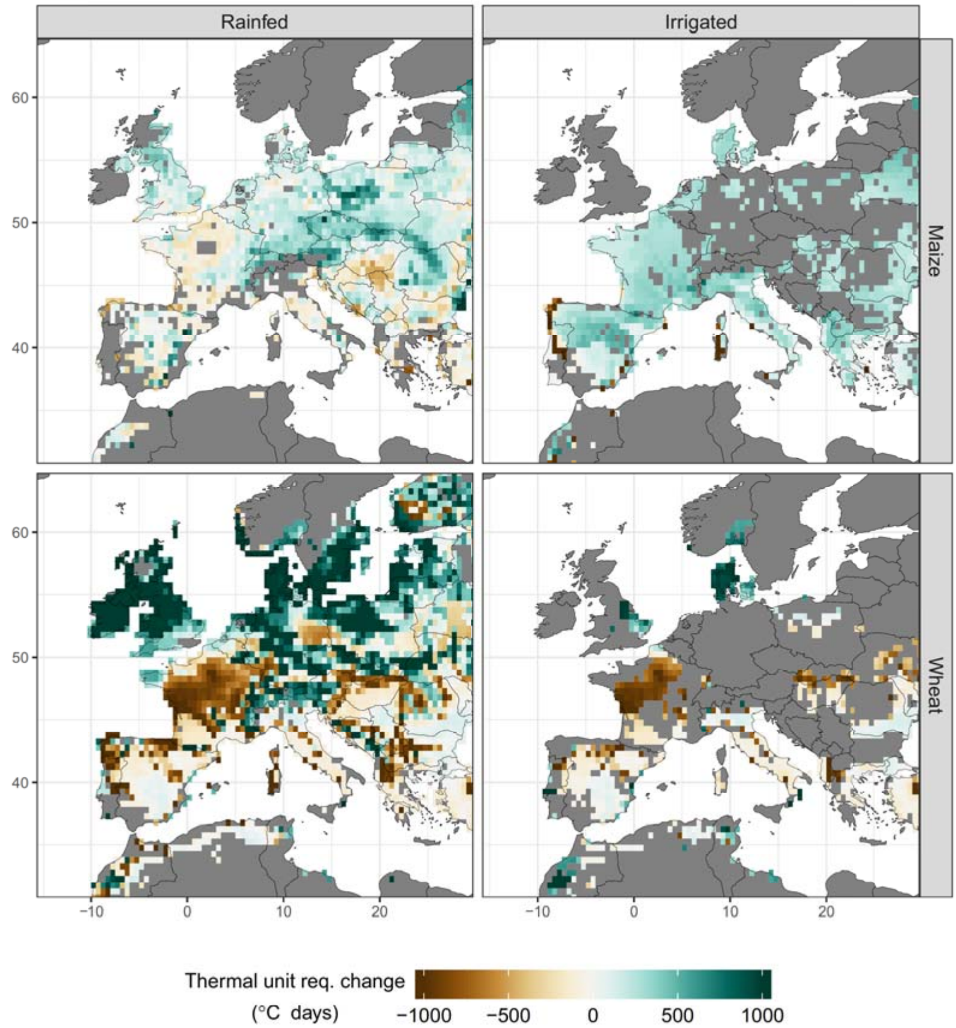


Figure S11: European focus of maize and wheat cultivar change, for irrigated and rainfed areas, to allow for comparison with Zimmermann et al. (2017) and Parent et al. (2018) results. Patterns of thermal unit requirements changes (°C days) between complete adaptation (2080-2099) and reference (1986-2005) scenarios. The legend scale is cut to the range -1000 to +1000 °C days to highlight smaller differences and allow comparison between the two crops. Area that is not part of present cropland is depicted in gray.

References

Abdulai, A. L., M. Kouressy, M. Vaksmann, F. Asch, M. Giese, and B. Holger (2012). "Latitude and date of sowing influences phenology of photoperiod-sensitive sorghums". In: *Journal of agronomy and crop science* 198.5, pp. 340–348.

Aggarwal, P., S. Vyas, P. Thornton, and B. M. Campbell (2019). "How much does climate change add to the challenge of feeding the planet this century?" In: *Environmental Research Letters* 14.4, p. 043001. DOI: 10.1088/1748-9326/aafa3e.

Ainsworth, E. A. and D. R. Ort (2010). "How Do We Improve Crop Production in a Warming World?" In: *Plant Physiology* 154.2, pp. 526–530. DOI: 10.1104/pp.110.161349.

Altieri, M. A. and C. I. Nicholls (2017). "The adaptation and mitigation potential of traditional agriculture in a changing climate". In: *Climatic Change* 140.1, pp. 33–45.

Antle, J. M. (2019). "Data, Economics and Computational Agricultural Science". In: *American Journal of Agricultural Economics* 101.2, pp. 365–382. DOI: 10.1093/ajae/aay103.

Araya, A., S. D. Keesstra, and L. Stroosnijder (2010). "A new agro-climatic classification for crop suitability zoning in northern semi-arid Ethiopia". In: *Agricultural and Forest Meteorology* 150.7-8, pp. 1057–1064. DOI: 10.1016/j.agrformet.2010.04.003.

Archontoulis, S. V., F. E. Miguez, and K. J. Moore (2014). "A methodology and an optimization tool to calibrate phenology of short-day species included in the APSIM PLANT model: Application to soybean". In: *Environmental Modelling & Software* 62, pp. 465–477. DOI: 10.1016/j.envsoft.2014.04.009.

Asseng, S. et al. (2014). "Rising temperatures reduce global wheat production". In: *Nature Climate Change* 5.2, pp. 143–147. DOI: 10.1038/nclimate2470.

Asseng, S., Y. Zhu, E. Wang, and W. Zhang (2015). "Crop modeling for climate change impact and adaptation". In: *Crop Physiology.* Elsevier, pp. 505–546. DOI: 10.1016/b978-0-12-417104-6.00020-0.

Asseng, S. et al. (2018). "Climate change impact and adaptation for wheat protein". In: *Global Change Biology* 25.1, pp. 155–173. DOI: 10.1111/gcb.14481.

Atkin, O. K., D. Bruhn, V. M. Hurry, and M. G. Tjoelker (2005). "Evans Review No. 2: The hot and the cold: unravelling the variable response of plant respiration to temperature". In: *Functional Plant Biology* 32.2, pp. 87–105.

Atkin, O. K. and M. G. Tjoelker (2003). "Thermal acclimation and the dynamic response of plant respiration to temperature". In: *Trends in plant science* 8.7, pp. 343–351.

Aubry, C., F Papy, and A Capillon (1998). "Modelling decision-making processes for annual crop management". In: *Agricultural systems* 56.1, pp. 45–65.

Balesdent, J., I. Basile-Doelsch, J. Chadoeuf, S. Cornu, D. Derrien, Z. Fekiacova, and C. Hatté (2018). "Atmosphere–soil carbon transfer as a function of soil depth". In: *Nature* 559.7715, pp. 599–602. DOI: 10.1038/s41586-018-0328-3.

Barber, H. M., J. Carney, F. Alghabari, and M. J. Gooding (2015). "Decimal growth stages for precision wheat production in changing environments?" In: *Annals of Applied Biology* 166.3, pp. 355–371. DOI: 10.1111/aab.12207.

Barbottin, A., M. L. Bail, and M. H. Jeuffroy (2006). "The Azodyn crop model as a decision support tool for choosing cultivars". In: *Agronomy for Sustainable Development* 26.2, pp. 107–115. DOI: 10.1051/agro:2006003.

Barnabás, B., K. Jäger, and A. Fehér (2007). "The effect of drought and heat stress on reproductive processes in cereals". In: *Plant, Cell & Environment* 0.0, pp. 11–38. DOI: 10.1111/j.1365-3040.2007.01727.x.

Bassu, S., S. Asseng, R. Motzo, and F. Giunta (2009). "Optimising sowing date of durum wheat in a variable Mediterranean environment". In: *Field Crops Research* 111.1-2, pp. 109–118. DOI: 10.1016/j.fcr.2008.11.002.

Bodirsky, B. L., S. Rolinski, A. Biewald, I. Weindl, A. Popp, and H. Lotze-Campen (2015). "Global Food Demand Scenarios for the 21st Century". In: *PLOS ONE* 10.11. Ed. by A. Belgrano, e0139201. DOI: 10.1371/journal.pone.0139201.

Bodner, G., A. Nakhforoosh, and H.-P. Kaul (2015). "Management of crop water under drought: a review". In: *Agronomy for Sustainable Development* 35.2, pp. 401–442.

Bondeau, A., P. C. Smith, S. zaehle, S. Schaphoff, W. Lucht, W. Cramer, D. Gerten, H. Lotze-Campen, C. Müller, M. Reichstein, and B. Smith (2007). "Modelling the role of agriculture for the 20th century global terrestrial carbon balance". In: *Global Change Biology* 13.3, pp. 679–706. DOI: 10.1111/j.1365-2486.2006.01305.x.

Bonsch, M., A. Popp, A. Biewald, S. Rolinski, C. Schmitz, I. Weindl, M. Stevanovic, K. Högner, J. Heinke, S. Ostberg, J. P. Dietrich, B. Bodirsky, H. Lotze-Campen, and F. Humpenöder (2015). "Environmental flow provision: Implications for agricultural water and land-use at the global scale". In: *Global Environmental Change* 30, pp. 113–132. DOI: 10.1016/j.gloenvcha.2014.10.015.

Burke, K. D., J. W. Williams, M. A. Chandler, A. M. Haywood, D. J. Lunt, and B. L. Otto-Bliesner (2018). "Pliocene and Eocene provide best analogs for near-future climates". In: *Proceedings of the National Academy of Sciences* 115.52, pp. 13288–13293. DOI: 10.1073/pnas.1809600115.

Burke, M. and K. Emerick (2016). "Adaptation to climate change: Evidence from US agriculture". In: *American Economic Journal: Economic Policy* 8.3, pp. 106–40.

Butler, E. E. and P. Huybers (2013). "Adaptation of US maize to temperature variations". In: *Nature Climate Change* 3.1, pp. 68–72.

Butler, E. E., N. D. Mueller, and P. Huybers (2018). "Peculiarly pleasant weather for US maize". In: *Proceedings of the National Academy of Sciences* 115.47, pp. 11935–11940. DOI: 10.1073/pnas.1808035115.

Calanca, P. (2014). "Weather Forecasting Applications in Agriculture". In: *Encyclopedia of Agriculture and Food Systems*. Elsevier, pp. 437–449. DOI: 10.1016/b978-0-444-52512-3.00234-5.

Cammarano, D., B. Basso, L. Stefanova, and P. Grace (2012). “Adapting wheat sowing dates to projected climate change in the Australian subtropics: analysis of crop water use and yield”. In: *Crop and Pasture Science* 63.10, p. 974. DOI: 10.1071/cp11324.

Carter, E. K., J. Melkonian, S. J. Riha, and S. B. Shaw (2016). “Separating heat stress from moisture stress: analyzing yield response to high temperature in irrigated maize”. In: *Environmental Research Letters* 11.9, p. 094012.

Certini, G. and R. Scalenghe (2015). “Holocene as Anthropocene”. In: *Science* 349.6245, pp. 246–246. DOI: 10.1126/science.349.6245.246-a.

Challinor, A. J., J. Watson, D. B. Lobell, S. M. Howden, D. R. Smith, and N. Chhetri (2014). “A meta-analysis of crop yield under climate change and adaptation”. In: *Nature Climate Change* 4.4, pp. 287–291. DOI: 10.1038/nclimate2153.

Challinor, A. J., A.-K. Koehler, J. Ramirez-Villegas, S. Whitfield, and B. Das (2016). “Current warming will reduce yields unless maize breeding and seed systems adapt immediately”. In: *Nature Climate Change* 6.10, p. 954.

Challinor, A. J., C. Müller, S. Asseng, C. Deva, K. J. Nicklin, D. Wallach, E. Vanuytrecht, S. Whitfield, J. Ramirez-Villegas, and A.-K. Koehler (2018). “Improving the use of crop models for risk assessment and climate change adaptation”. In: *Agricultural Systems* 159, pp. 296–306. DOI: 10.1016/j.agsy.2017.07.010.

Chenu, K., J. R. Porter, P. Martre, B. Basso, S. C. Chapman, F. Ewert, M. Bindi, and S. Asseng (2017). “Contribution of crop models to adaptation in wheat”. In: *Trends in plant science* 22.6, pp. 472–490.

Christidis, N., G. S. Jones, and P. A. Stott (2014). “Dramatically increasing chance of extremely hot summers since the 2003 European heatwave”. In: *Nature Climate Change* 5.1, pp. 46–50. DOI: 10.1038/nclimate2468.

Ciais, P., M. Reichstein, N. Viovy, A. Granier, J. Ogée, V. Allard, M. Aubinet, N. Buchmann, C. Bernhofer, A. Carrara, F. Chevallier, N. D. Noblet, A. D. Friend, P. Friedlingstein, T. Grünwald, B. Heinesch, P. Keronen, A. Knohl, G. Krinner, D. Loustau, G. Manca, G. Matteucci, F. Miglietta, J. M. Ourcival, D. Papale, K. Pilegaard, S. Rambal, G. Seufert, J. F. Soussana, M. J. Sanz, E. D. Schulze, T. Vesala, and R. Valentini (2005). “Europe-wide reduction in primary productivity caused by the heat and drought in 2003”. In: *Nature* 437.7058, pp. 529–533. DOI: 10.1038/nature03972.

Clerget, B., M. Dingkuhn, E. Goze, H. F. W. Rattunde, and B. Ney (2008). “Variability of Phyllochron, Plastochron and Rate of Increase in Height in Photoperiod-sensitive Sorghum Varieties”. In: *Annals of Botany* 101.4, pp. 579–594. DOI: 10.1093/aob/mcm327.

Conant, R. T., A. B. Berdanier, and P. R. Grace (2013). “Patterns and trends in nitrogen use and nitrogen recovery efficiency in world agriculture”. In: *Global Biogeochemical Cycles* 27.2, pp. 558–566. DOI: 10.1002/gbc.20053.

Cramer, G. R., K. Urano, S. Delrot, M. Pezzotti, and K. Shinozaki (2011). “Effects of abiotic stress on plants: a systems biology perspective”. In: *BMC Plant Biology* 11.1, p. 163. DOI: 10.1186/1471-2229-11-163.

Craufurd, P. Q. and A. Qi (2001). “Photothermal adaptation of sorghum (Sorghum bicolour) in Nigeria”. In: *Agricultural and Forest Meteorology* 108.3, pp. 199–211. DOI: 10.1016/s0168-1923(01)00241-6.

Craufurd, P. Q. and T. R. Wheeler (2009). “Climate change and the flowering time of annual crops”. In: *Journal of Experimental Botany* 60.9, pp. 2529–2539. DOI: 10.1093/jxb/erp196.

Dalgaard, T., N. J. Hutchings, and J. R. Porter (2003). “Agroecology, scaling and interdisciplinarity”. In: *Agriculture, Ecosystems & Environment* 100.1, pp. 39–51. DOI: 10.1016/s0167-8809(03)00152-x.

Daryanto, S., L. Wang, and P.-A. Jacinthe (2017). “Global synthesis of drought effects on cereal, legume, tuber and root crops production: A review”. In: *Agricultural Water Management* 179, pp. 18–33. DOI: 10.1016/j.agwat.2016.04.022.

Davin, E. L., S. I. Seneviratne, P. Ciais, A. Olioso, and T. Wang (2014). “Preferential cooling of hot extremes from cropland albedo management”. In: *Proceedings of the National Academy of Sciences* 111.27, pp. 9757–9761. DOI: 10.1073/pnas.1317323111.

Debaeke, P. and A. Aboudrare (2004). “Adaptation of crop management to water-limited environments”. In: *European Journal of Agronomy* 21.4, pp. 433–446. DOI: 10.1016/j.eja.2004.07.006.

Dee, D. P., S. M. Uppala, A. J. Simmons, P. Berrisford, P. Poli, S. Kobayashi, U. Andrae, M. Balmaseda, G. Balsamo, P. Bauer, et al. (2011). “The ERA-Interim reanalysis: Configuration and performance of the data assimilation system”. In: *Quarterly Journal of the royal meteorological society* 137.656, pp. 553–597.

Deryng, D., W. J. Sacks, C. C. Barford, and N. Ramankutty (2011). “Simulating the effects of climate and agricultural management practices on global crop yield”. In: *Global Biogeochemical Cycles* 25.2, n/a–n/a. DOI: 10.1029/2009gb003765.

Deryng, D., D. Conway, N. Ramankutty, J. Price, and R. Warren (2014). “Global crop yield response to extreme heat stress under multiple climate change futures”. In: *Environmental Research Letters* 9.3, p. 034011. DOI: 10.1088/1748-9326/9/3/034011.

Deryng, D., J. Elliott, C. Folberth, C. Müller, T. A. M. Pugh, K. J. Boote, D. Conway, A. C. Ruane, D. Gerten, J. W. Jones, et al. (2016). “Regional disparities in the beneficial effects of rising CO 2 concentrations on crop water productivity”. In: *Nature Climate Change* 6.8, p. 786.

Deutsch, C. A., J. J. Tewksbury, M. Tigchelaar, D. S. Battisti, S. C. Merrill, R. B. Huey, and R. L. Naylor (2018). “Increase in crop losses to insect pests in a warming climate”. In: *Science* 361.6405, pp. 916–919. DOI: 10.1126/science.aat3466.

Di Paola, A., R. Valentini, and M. Santini (2015). “An overview of available crop growth and yield models for studies and assessments in agriculture”. In: *Journal of the Science of Food and Agriculture* 96.3, pp. 709–714. DOI: 10.1002/jsfa.7359.

Dietrich, J. P., C. Schmitz, H. Lotze-Campen, A. Popp, and C. Müller (2014). “Forecasting technological change in agriculture—An endogenous implementation in a global land use model”. In: *Technological Forecasting and Social Change* 81, pp. 236–249. DOI: 10.1016/j.techfore.2013.02.003.

Dillon, A., K. McGee, and G. Oseni (2015). “Agricultural Production, Dietary Diversity and Climate Variability”. In: *The Journal of Development Studies* 51.8, pp. 976–995. DOI: 10.1080/00220388.2015.1018902.

Distelfeld, A., C. Li, and J. Dubcovsky (2009). "Regulation of flowering in temperate cereals". In: *Current Opinion in Plant Biology* 12.2, pp. 178–184. DOI: 10.1016/j.pbi.2008.12.010.

Dlugokencky, E. and P. Tans (2019). *Trends in atmospheric carbon dioxide, National Oceanic & Atmospheric Administration, Earth System Research Laboratory (NOAA/ESRL)*. data available at: http://www.esrl.noaa.gov/gmd/ccgg/trends/global.html, accessed on: 18th August 2019.

Dobor, L., Z. Barcza, T. Hlásny, T. Árendás, T. Spitkó, and N. Fodor (2016). "Crop planting date matters: Estimation methods and effect on future yields". In: *Agricultural and Forest Meteorology* 223, pp. 103–115. DOI: 10.1016/j.agrformet.2016.03.023.

Donohue, R. J., T. R. McVicar, and M. L. Roderick (2010). "Assessing the ability of potential evaporation formulations to capture the dynamics in evaporative demand within a changing climate". In: *Journal of Hydrology* 386.1-4, pp. 186–197.

Doré, T., D. Makowski, E. Malézieux, N. Munier-Jolain, M. Tchamitchian, and P. Tittonell (2011). "Facing up to the paradigm of ecological intensification in agronomy: Revisiting methods, concepts and knowledge". In: *European Journal of Agronomy* 34.4, pp. 197–210. DOI: 10.1016/j.eja.2011.02.006.

Dowle, M. and A. Srinivasan (2017). *data.table: Extension of 'data.frame'*. R package version 1.10.4-3.

Drewniak, B., J. Song, J. Prell, V. R. Kotamarthi, and R. Jacob (2013). "Modeling agriculture in the Community Land Model". In: *Geoscientific Model Development* 6.2, pp. 495–515. DOI: 10.5194/gmd-6-495-2013.

Dury, J., N. Schaller, F. Garcia, A. Reynaud, and J. E. Bergez (2011a). "Models to support cropping plan and crop rotation decisions. A review". In: *Agronomy for Sustainable Development* 32.2, pp. 567–580. DOI: 10.1007/s13593-011-0037-x.

Dury, M., A. Hambuckers, P Warnant, A. Henrot, E Favre, M. Ouberdous, and L. François (2011b). "Responses of European forest ecosystems to 21 (st) century climate: assessing changes in interannual variability and fire intensity". In: *iForest: Biogeosciences and Forestry* 4, pp. 82–99.

Egli, D. B. (2011). "Time and the Productivity of Agronomic Crops and Cropping Systems". In: *Agronomy Journal* 103.3, p. 743. DOI: 10.2134/agronj2010.0508.

Elliott, J., C. Müller, D. Deryng, J. Chryssanthacopoulos, K. J. Boote, M. Büchner, I. Foster, M. Glotter, J. Heinke, T. Iizumi, R. C. Izaurralde, N. D. Mueller, D. K. Ray, C. Rosenzweig, A. C. Ruane, and J. Sheffield (2015). "The Global Gridded Crop Model Intercomparison: data and modeling protocols for Phase 1 (v1.0)". In: *Geoscientific Model Development* 8.2, pp. 261–277. DOI: 10.5194/gmd-8-261-2015.

Elliott, J., D. Deryng, C. Müller, K. Frieler, M. Konzmann, D. Gerten, M. Glotter, M. Flörke, Y. Wada, N. Best, et al. (2014). "Constraints and potentials of future irrigation water availability on agricultural production under climate change". In: *Proceedings of the National Academy of Sciences* 111.9, pp. 3239–3244.

Elliott, J., M. Glotter, A. C. Ruane, K. J. Boote, J. L. Hatfield, J. W. Jones, C. Rosenzweig, L. A. Smith, and I. Foster (2018). "Characterizing agricultural impacts of recent large-scale

US droughts and changing technology and management". In: *Agricultural Systems* 159, pp. 275–281. DOI: 10.1016/j.agsy.2017.07.012.

Elliott, J., D. Kelly, N. Best, M. Wilde, M. Glotter, and I. Foster (2013). "The parallel system for integrating impact models and sectors (pSIMS)". In: *Proceedings of the Conference on Extreme Science and Engineering Discovery Environment: Gateway to Discovery*. ACM, p. 21.

Erb, K.-H., S. Luyssaert, P. Meyfroidt, J. Pongratz, A. Don, S. Kloster, T. Kuemmerle, T. Fetzel, R. Fuchs, M. Herold, H. Haberl, C. D. Jones, E. Marín-Spiotta, I. McCallum, E. Robertson, V. Seufert, S. Fritz, A. Valade, A. Wiltshire, and A. J. Dolman (2016). "Land management: data availability and process understanding for global change studies". In: *Global Change Biology* 23.2, pp. 512–533. DOI: 10.1111/gcb.13443.

Estrella, N., T. H. Sparks, and A. Menzel (2009). "Effects of temperature, phase type and timing, location, and human density on plant phenological responses in Europe". In: *Climate Research* 39, pp. 235–248. DOI: 10.3354/cr00818.

Estrella, N., T. H. sparks, and A. Menzel (2007). "Trends and temperature response in the phenology of crops in Germany". In: *Global Change Biology* 13.8, pp. 1737–1747. DOI: 10.1111/j.1365-2486.2007.01374.x.

Fader, M., S. Rost, C. Müller, A. Bondeau, and D. Gerten (2010). "Virtual water content of temperate cereals and maize: Present and potential future patterns". In: *Journal of Hydrology* 384.3-4, pp. 218–231. DOI: 10.1016/j.jhydrol.2009.12.011.

Farooq, M., H. Bramley, J. A. Palta, and K. H. Siddique (2011). "Heat Stress in Wheat during Reproductive and Grain-Filling Phases". In: *Critical Reviews in Plant Sciences* 30.6, pp. 491–507. DOI: 10.1080/07352689.2011.615687.

Fath, B. (2018). *Encyclopedia of Ecology*. Elsevier Science. ISBN: 9780444641304.

Fischer, R. A. (2015). "Definitions and determination of crop yield, yield gaps, and of rates of change". In: *Field Crops Research* 182, pp. 9–18. DOI: 10.1016/j.fcr.2014.12.006.

Fishman, R. (2016). "More uneven distributions overturn benefits of higher precipitation for crop yields". In: *Environmental Research Letters* 11.2, p. 024004. DOI: 10.1088/1748-9326/11/2/024004.

Folberth, C., J. Elliott, C. Müller, J. Balkovic, J. Chryssanthacopoulos, R. C. Izaurralde, C. D. Jones, N. Khabarov, W. Liu, A. Reddy, et al. (2016). "Uncertainties in global crop model frameworks: effects of cultivar distribution, crop management and soil handling on crop yield estimates". In: *Biogeosciences Discussions*, pp. 1–30.

Folberth, C., T. Gaiser, K. C. Abbaspour, R. Schulin, and H. Yang (2012). "Regionalization of a large-scale crop growth model for sub-Saharan Africa: Model setup, evaluation, and estimation of maize yields". In: *Agriculture, ecosystems & environment* 151, pp. 21–33.

Foley, J. A. (2005). "Global Consequences of Land Use". In: *Science* 309.5734, pp. 570–574. DOI: 10.1126/science.1111772.

Folke, C., S. Carpenter, B. Walker, M. Scheffer, T. Chapin, and J. Rockström (2010). "Resilience thinking: integrating resilience, adaptability and transformability". In: *Ecology and society* 15.4.

Food and Agriculture Organization (2001). *Food Balance Sheets A Handbook*. Rome, Italy. URL: http://www.fao.org/docrep/003/x9892e/X9892e05.htm#P8217_125315.

Food and Agriculture Organization (2018). *The future of food and agriculture - Alternative pathways to 2050.* Licence: CC BY-NC-SA 3.0 IGO. Rome, Italy. URL: http://www.fao.org/3/CA1553EN/ca1553en.pdf.

Frieler, K., B. Schauberger, A. Arneth, J. Balkovič, J. Chryssanthacopoulos, D. Deryng, J. Elliott, C. Folberth, N. Khabarov, C. Müller, S. Olin, T. A. M. Pugh, S. Schaphoff, J. Schewe, E. Schmid, L. Warszawski, and A. Levermann (2017a). "Understanding the weather signal in national crop-yield variability". In: *Earth's Future* 5.6, pp. 605–616. DOI: 10.1002/2016ef000525.

Frieler, K. et al. (2017b). "Assessing the impacts of 1.5°C global warming – simulation protocol of the Inter-Sectoral Impact Model Intercomparison Project (ISIMIP2b)". In: *Geoscientific Model Development* 10.12, pp. 4321–4345. DOI: 10.5194/gmd-10-4321-2017.

Füssel, H.-M. (2007). "Adaptation planning for climate change: concepts, assessment approaches, and key lessons". In: *Sustainability Science* 2.2, pp. 265–275. DOI: 10.1007/s11625-007-0032-y.

Galloway, J. N., J. D. Aber, J. W. Erisman, S. P. Seitzinger, R. W. Howarth, E. B. Cowling, and B. J. Cosby (2003). "The Nitrogen Cascade". In: *BioScience* 53.4, p. 341. DOI: 10.1641/0006-3568(2003)053[0341:tnc]2.0.co;2.

Gerten, D., H. Hoff, J. Rockström, J. Jägermeyr, M. Kummu, and A. V. Pastor (2013). "Towards a revised planetary boundary for consumptive freshwater use: role of environmental flow requirements". In: *Current Opinion in Environmental Sustainability* 5.6, pp. 551–558. DOI: 10.1016/j.cosust.2013.11.001.

Gerten, D., S. Schaphoff, U. Haberlandt, W. Lucht, and S. Sitch (2004). "Terrestrial vegetation and water balance—hydrological evaluation of a dynamic global vegetation model". In: *Journal of Hydrology* 286.1-4, pp. 249–270. DOI: 10.1016/j.jhydrol.2003.09.029.

Gliessman, S. R. (2014). *Agroecology: the ecology of sustainable food systems.* CRC press.

Glotter, M. and J. Elliott (2016). "Simulating US agriculture in a modern Dust Bowl drought". In: *Nature Plants* 3.1. DOI: 10.1038/nplants.2016.193.

Godfray, H. C. J., J. R. Beddington, I. R. Crute, L. Haddad, D. Lawrence, J. F. Muir, J. Pretty, S. Robinson, S. M. Thomas, and C. Toulmin (2010). "Food Security: The Challenge of Feeding 9 Billion People". In: *Science* 327.5967, pp. 812–818. DOI: 10.1126/science.1185383.

Godwin, R. J., G. A. Wood, J. C. Taylor, S. M. Knight, and J. P. Welsh (2003). "Precision farming of cereal crops: a review of a six year experiment to develop management guidelines". In: *Biosystems Engineering* 84.4, pp. 375–391.

Gourdji, S. M., A. M. Sibley, and D. B. Lobell (2013). "Global crop exposure to critical high temperatures in the reproductive period: historical trends and future projections". In: *Environmental Research Letters* 8.2, p. 024041. DOI: 10.1088/1748-9326/8/2/024041.

Grassini, P., K. M. Eskridge, and K. G. Cassman (2013). "Distinguishing between yield advances and yield plateaus in historical crop production trends". In: *Nature Communications* 4.1. DOI: 10.1038/ncomms3918.

Hank, T. B., H. Bach, and W. Mauser (2015). "Using a remote sensing-supported hydro-agroecological model for field-scale simulation of heterogeneous crop growth and yield: application for wheat in central Europe". In: *Remote Sensing* 7.4, pp. 3934–3965.

Hansen, J. (2005). “Earth's Energy Imbalance: Confirmation and Implications”. In: *Science* 308.5727, pp. 1431–1435. DOI: 10.1126/science.1110252.

Hatfield, J. L., K. J. Boote, B. A. Kimball, L. H. Ziska, R. C. Izaurralde, D. Ort, A. M. Thomson, and D. Wolfe (2011a). “Climate Impacts on Agriculture: Implications for Crop Production”. In: *Agronomy Journal* 103.2, p. 351. DOI: 10.2134/agronj2010.0303.

Hatfield, J. L., L. Wright-Morton, and B. Hall (2018). “Vulnerability of grain crops and croplands in the Midwest to climatic variability and adaptation strategies”. In: *Climatic change* 146.1-2, pp. 263–275.

Hatfield, J. L. (2016). “Increased temperatures have dramatic effects on growth and grain yield of three maize hybrids”. In: *Agricultural & Environmental Letters* 1.1.

Hatfield, J. L., K. J. Boote, B. A. Kimball, L. H. Ziska, R. C. Izaurralde, D. Ort, A. M. Thomson, and D. Wolfe (2011b). “Climate impacts on agriculture: implications for crop production”. In: *Agronomy journal* 103.2, pp. 351–370.

Hatfield, J. L. and J. H. Prueger (2015). “Temperature extremes: Effect on plant growth and development”. In: *Weather and Climate Extremes* 10, pp. 4–10. DOI: 10.1016/j.wace.2015.08.001.

Hay, R. K. M., J. R. Porter, et al. (2006). *The physiology of crop yield.* Blackwell Publishing.

Herrero, M., P. K. Thornton, B. Power, J. R. Bogard, R. Remans, S. Fritz, J. S. Gerber, G. Nelson, L. See, K. Waha, et al. (2017). “Farming and the geography of nutrient production for human use: a transdisciplinary analysis”. In: *The Lancet Planetary Health* 1.1, e33–e42.

Hunt, J. R., J. M. Lilley, B. Trevaskis, B. M. Flohr, A. Peake, A. Fletcher, A. B. Zwart, D. Gobbett, and J. A. Kirkegaard (2019). “Early sowing systems can boost Australian wheat yields despite recent climate change”. In: *Nature Climate Change* 9.3, pp. 244–247. DOI: 10.1038/s41558-019-0417-9.

Hutchings, N. J., G. J. Reinds, A. Leip, M. Wattenbach, J. F. Bienkowski, T. Dalgaard, U. Dragosits, J. L. Drouet, P. Durand, O. Maury, and W. de Vries (2012). “A model for simulating the timelines of field operations at a European scale for use in complex dynamic models”. In: *Biogeosciences* 9.11, pp. 4487–4496. DOI: 10.5194/bg-9-4487-2012.

IFPRI (2009). *Climate change: Impact on agriculture and costs of adaptation.* Tech. rep. International Food Policy Research Institute. DOI: 10.2499/0896295354.

Iizumi, T., W. Kim, and M. Nishimori (2019). “Modeling the Global Sowing and Harvesting Windows of Major Crops Around the Year 2000”. In: *Journal of Advances in Modeling Earth Systems* 11.1, pp. 99–112. DOI: 10.1029/2018ms001477.

IPCC (2013). *Climate Change 2013: The Physical Science Basis. Contribution of Working Group I to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change.* Cambridge, United Kingdom and New York, NY, USA: Cambridge University Press, p. 1535. ISBN: ISBN 978-1-107-66182-0. DOI: 10.1017/CBO9781107415324.

IPCC (2014). *Climate Change 2014: Impacts, Adaptation, and Vulnerability. Part A: Global and Sectoral Aspects. Contribution of Working Group II to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change.* Cambridge, United Kingdom and New York, NY, USA: Cambridge University Press, p. 1132.

IPCC (2018). *Global warming of 1.5 C. An IPCC Special Report on the impacts of global warming of 1.5 C above pre-industrial levels and related global greenhouse gas emission* *pathways, in the context of strengthening the global response to the threat of climate change, sustainable development, and efforts to eradicate poverty.* Cambridge, United Kingdom and New York, NY, USA: Cambridge University Press.

Jachner, S., G. Boogaart, and T. Petzoldt (2007). “Statistical Methods for the Qualitative Assessment of Dynamic Models with Time Delay (RPackagequalV)”. In: *Journal of Statistical Software* 22.8. DOI: `10.18637/jss.v022.i08`.

Jägermeyr, J. and K. Frieler (2018). “Spatial variations in crop growing seasons pivotal to reproduce global fluctuations in maize and wheat yields”. In: *Science Advances* 4.11, eaat4517. DOI: `10.1126/sciadv.aat4517`.

Jägermeyr, J., D. Gerten, S. Schaphoff, J. Heinke, W. Lucht, and J. Rockström (2016). “Integrated crop water management might sustainably halve the global food gap”. In: *Environmental Research Letters* 11.2, p. 025002. DOI: `10.1088/1748-9326/11/2/025002`.

Jones, J. W., J. M. Antle, B. Basso, K. J. Boote, R. T. Conant, I. Foster, H. C. J. Godfray, M. Herrero, R. E. Howitt, S. Janssen, B. A. Keating, R. Munoz-Carpena, C. H. Porter, C. Rosenzweig, and T. R. Wheeler (2017). “Brief history of agricultural systems modeling”. In: *Agricultural Systems* 155, pp. 240–254. DOI: `10.1016/j.agsy.2016.05.014`.

Jones, J. W., G. Hoogenboom, C. H. Porter, K. J. Boote, W. D. Batchelor, L. A. Hunt, P. W. Wilkens, U. Singh, A. J. Gijsman, and J. T. Ritchie (2003). “The DSSAT cropping system model”. In: *European journal of agronomy* 18.3-4, pp. 235–265.

Kaaya, A. N., H. L. Warren, S. Kyamanywa, and W. Kyamuhangire (2005). “The effect of delayed harvest on moisture content, insect damage, moulds and aflatoxin contamination of maize in Mayuge district of Uganda”. In: *Journal of the Science of Food and Agriculture* 85.15, pp. 2595–2599. DOI: `10.1002/jsfa.2313`.

Kahiluoto, H., J. Kaseva, J. Balek, J. E. Olesen, M. Ruiz-Ramos, A. Gobin, K. C. Kersebaum, J. Takáč, F. Ruget, R. Ferrise, P. Bezak, G. Capellades, C. Dibari, H. Mäkinen, C. Nendel, D. Ventrella, A. Rodríguez, M. Bindi, and M. Trnka (2018). “Decline in climate resilience of European wheat”. In: *Proceedings of the National Academy of Sciences* 116.1, pp. 123–128. DOI: `10.1073/pnas.1804387115`.

Kamran, A., M. Iqbal, and D. Spaner (2014). “Flowering time in wheat (Triticum aestivum L.): a key factor for global adaptability”. In: *Euphytica* 197.1, pp. 1–26. DOI: `10.1007/s10681-014-1075-7`.

Karapinar, B. and G. Özertan (2019). “Yield implications of date and cultivar adaptation to wheat phenological shifts: a survey of farmers in Turkey”. In: *Climatic Change*. DOI: `10.1007/s10584-019-02532-4`.

Kates, R. W., W. R. Travis, and T. J. Wilbanks (2012). “Transformational adaptation when incremental adaptations to climate change are insufficient”. In: *Proceedings of the National Academy of Sciences* 109.19, pp. 7156–7161. DOI: `10.1073/pnas.1115521109`.

Khush, G. S., D. P. Garrity, et al. (1984). *Terminology for rice growing environments.*

Khush, G. S. (2001). “Green revolution: the way forward”. In: *Nature reviews genetics* 2.10, p. 815.

Kimball, B. A. (2016). “Crop responses to elevated CO2 and interactions with H2O, N, and temperature”. In: *Current opinion in plant biology* 31, pp. 36–43.

King, M., D. Altdorff, P. Li, L. Galagedara, J. Holden, and A. Unc (2018). “Northward shift of the agricultural climate zone under 21st-century global climate change”. In: *Scientific Reports* 8.1. DOI: 10.1038/s41598-018-26321-8.

Koehler, A.-K., A. J. Challinor, E. Hawkins, and S. Asseng (2013). “Influences of increasing temperature on Indian wheat: quantifying limits to predictability”. In: *Environmental Research Letters* 8.3, p. 034016. DOI: 10.1088/1748-9326/8/3/034016.

Kollas, C., K. C. Kersebaum, C. Nendel, K. Manevski, C. Müller, T. Palosuo, C. M. Armas-Herrera, N. Beaudoin, M. Bindi, M. Charfeddine, T. Conradt, J. Constantin, J. Eitzinger, F. Ewert, R. Ferrise, T. Gaiser, I. G. de Cortazar-Atauri, L. Giglio, P. Hlavinka, H. Hoffmann, M. P. Hoffmann, M. Launay, R. Manderscheid, B. Mary, W. Mirschel, M. Moriondo, J. E. Olesen, I. Öztürk, A. Pacholski, D. Ripoche-Wachter, P. P. Roggero, S. Roncossek, R. P. Rötter, F. Ruget, B. Sharif, M. Trnka, D. Ventrella, K. Waha, M. Wegehenkel, H.-J. Weigel, and L. Wu (2015). “Crop rotation modelling—A European model intercomparison”. In: *European Journal of Agronomy* 70, pp. 98–111. DOI: 10.1016/j.eja.2015.06.007.

Kucharik, C. J. (2006). “A multidecadal trend of earlier corn planting in the central USA”. In: *Agronomy Journal* 98.6, pp. 1544–1550.

Kucharik, C. J. and K. R. Brye (2003). “Integrated BIosphere Simulator (IBIS) Yield and Nitrate Loss Predictions for Wisconsin Maize Receiving Varied Amounts of Nitrogen Fertilizer”. In: *Journal of Environment Quality* 32.1, p. 247. DOI: 10.2134/jeq2003.2470.

Lal, R. (2004). “Soil Carbon Sequestration Impacts on Global Climate Change and Food Security”. In: *Science* 304.5677, pp. 1623–1627. DOI: 10.1126/science.1097396.

Langyintuo, A. S., W. Diallo, A. MacRobert, J. Dixon, and M J Banziger (2008). *An Analysis of the Bottlenecks affecting the production and deployment of maize seed in eastern and southern Africa.* CIMMYT.

Lawn, R. J., R. J. Summerfield, R. H. Ellis, A. Qi, E. H. Roberts, P. M. Chay, J. B. Brouwer, J. L. Rose, and S. J. Yeates (1995). “Towards the Reliable Prediction of Time to Flowering in Six Annual Crops. VI. Applications in Crop Improvement”. In: *Experimental Agriculture* 31.1, pp. 89–108. DOI: 10.1017/s0014479700025047.

Lawrence, D. M., G. C. Hurtt, A. Arneth, V. Brovkin, K. V. Calvin, A. D. Jones, C. D. Jones, P. J. Lawrence, N. de Noblet-Ducoudré, J. Pongratz, S. I. Seneviratne, and E. Shevliakova (2016). “The Land Use Model Intercomparison Project (LUMIP) contribution to CMIP6: rationale and experimental design”. In: *Geoscientific Model Development* 9.9, pp. 2973–2998. DOI: 10.5194/gmd-9-2973-2016.

Leng, G. and M. Huang (2017). “Crop yield response to climate change varies with crop spatial distribution pattern”. In: *Scientific Reports* 7.1. DOI: 10.1038/s41598-017-01599-2.

Li, Y., N. D. Noblet-Ducoudré, E. L. Davin, S. Motesharrei, N. Zeng, S. Li, and E. Kalnay (2016). “The role of spatial scale and background climate in the latitudinal temperature response to deforestation”. In: *Earth System Dynamics* 7.1, pp. 167–181. DOI: 10.5194/esd-7-167-2016.

Licker, R., M. Johnston, J. A. Foley, C. Barford, C. J. Kucharik, C. Monfreda, and N. Ramankutty (2010). “Mind the gap: how do climate and agricultural management explain the ‘yield gap’ of croplands around the world?” In: *Global Ecology and Biogeography* 19.6, pp. 769–782. DOI: 10.1111/j.1466-8238.2010.00563.x.

Lindeskog, M., A. Arneth, A. Bondeau, K. Waha, J. Seaquist, S. Olin, and B. Smith (2013). "Implications of accounting for land use in simulations of ecosystem carbon cycling in Africa". In: *Earth System Dynamics* 4.2, pp. 385–407. DOI: 10.5194/esd-4-385-2013.

Liu, B., S. Asseng, C. Müller, F. Ewert, J. Elliott, D. B. Lobell, P. Martre, A. C. Ruane, D. Wallach, J. W. Jones, et al. (2016a). "Similar estimates of temperature impacts on global wheat yield by three independent methods". In: *Nature Climate Change* 6.12, p. 1130.

Liu, J., J. R. Williams, A. J. Zehnder, and H. Yang (2007). "GEPIC–modelling wheat yield and crop water productivity with high resolution on a global scale". In: *Agricultural systems* 94.2, pp. 478–493.

Liu, W., H. Yang, C. Folberth, X. Wang, Q. Luo, and R. Schulin (2016b). "Global investigation of impacts of PET methods on simulating crop-water relations for maize". In: *Agricultural and forest meteorology* 221, pp. 164–175.

Liu, W., H. Yang, J. Liu, L. B. Azevedo, X. Wang, Z. Xu, K. C. Abbaspour, and R. Schulin (2016c). "Global assessment of nitrogen losses and trade-offs with yields from major crop cultivations". In: *Science of The Total Environment* 572, pp. 526–537.

Lobell, D. B. (2014). "Climate change adaptation in crop production: Beware of illusions". In: *Global Food Security* 3.2, pp. 72–76.

Lobell, D. B. and S. Asseng (2017). "Comparing estimates of climate change impacts from process-based and statistical crop models". In: *Environmental Research Letters* 12.1, p. 015001.

Lobell, D. B. and M. B. Burke (2010). "On the use of statistical models to predict crop yield responses to climate change". In: *Agricultural and Forest Meteorology* 150.11, pp. 1443–1452. DOI: 10.1016/j.agrformet.2010.07.008.

Lobell, D. B., K. G. Cassman, and C. B. Field (2009). "Crop Yield Gaps: Their Importance, Magnitudes, and Causes". In: *Annual Review of Environment and Resources* 34.1, pp. 179–204. DOI: 10.1146/annurev.environ.041008.093740.

Lobell, D. B., W. Schlenker, and J. Costa-Roberts (2011). "Climate Trends and Global Crop Production Since 1980". In: *Science* 333.6042, pp. 616–620. ISSN: 1095-9203. DOI: 10.1126/science.1204531.

Lombardozzi, D. L., G. B. Bonan, W. Wieder, A. S. Grandy, C. Morris, and D. L. Lawrence (2018). "Cover Crops May Cause Winter Warming in Snow-Covered Regions". In: *Geophysical Research Letters* 45.18, pp. 9889–9897. DOI: 10.1029/2018gl079000.

Long, S. P., E. A. Ainsworth, A. D. B. Leakey, and P. B. Morgan (2005). "Global food insecurity. Treatment of major food crops with elevated carbon dioxide or ozone under large-scale fully open-air conditions suggests recent models may have overestimated future yields". In: *Philosophical Transactions of the Royal Society B: Biological Sciences* 360.1463, pp. 2011–2020. DOI: 10.1098/rstb.2005.1749.

Lutz, F., T. Herzfeld, J. Heinke, S. Rolinski, S. Schaphoff, W. von Bloh, J. J. Stoorvogel, and C. Müller (2019). "Simulating the effect of tillage practices with the global ecosystem model LPJmL (version 5.0-tillage)". In: *Geoscientific Model Development* 12.6, pp. 2419–2440. DOI: 10.5194/gmd-12-2419-2019.

Lutz, F., J. J. Stoorvogel, and C. Müller (2019). “Options to model the effects of tillage on N2O emissions at the global scale”. In: *Ecological Modelling* 392, pp. 212–225. DOI: 10.1016/j.ecolmodel.2018.11.015.

Macholdt, J. and B. Honermeier (2016). “Impact of Climate Change on Cultivar Choice: Adaptation Strategies of Farmers and Advisors in German Cereal Production”. In: *Agronomy* 6.3, p. 40. DOI: 10.3390/agronomy6030040.

Makowski, D., T. Nesme, F. Papy, and T. Doré (2014). “Global agronomy, a new field of research. A review”. In: *Agronomy for Sustainable Development* 34.2, pp. 293–307. DOI: 10.1007/s13593-013-0179-0.

Mathison, C., C. Deva, P. Falloon, and A. J. Challinor (2018). “Estimating sowing and harvest dates based on the Asian summer monsoon”. In: *Earth System Dynamics* 9.2, pp. 563–592. DOI: 10.5194/esd-9-563-2018.

Mauser, W. and H. Bach (2009). “PROMET–Large scale distributed hydrological modelling to study the impact of climate change on the water flows of mountain watersheds”. In: *Journal of Hydrology* 376.3-4, pp. 362–377.

Mauser, W., G. Klepper, F. Zabel, R. Delzeit, T. Hank, B. Putzenlechner, and A. Calzadilla (2015). “Global biomass production potentials exceed expected future demand without the need for cropland expansion”. In: *Nature communications* 6, p. 8946.

McCarl, B. A. and T. W. Hertel (2018). “Climate Change as an Agricultural Economics Research Topic”. In: *Applied Economic Perspectives and Policy* 40.1, pp. 60–78. DOI: 10.1093/aepp/ppx052.

McDermid, S. S., L. O. Mearns, and A. C. Ruane (2017). “Representing agriculture in Earth System Models: Approaches and priorities for development”. In: *Journal of Advances in Modeling Earth Systems* 9.5, pp. 2230–2265. DOI: 10.1002/2016ms000749.

McSweeney, C. F. and R. G. Jones (2016). “How representative is the spread of climate projections from the 5 CMIP5 GCMs used in ISI-MIP?” In: *Climate Services* 1, pp. 24–29.

Mega, R., F. Abe, J.-S. Kim, Y. Tsuboi, K. Tanaka, H. Kobayashi, Y. Sakata, K. Hanada, H. Tsujimoto, J. Kikuchi, S. R. Cutler, and M. Okamoto (2019). “Tuning water-use efficiency and drought tolerance in wheat using abscisic acid receptors”. In: *Nature Plants* 5.2, pp. 153–159. DOI: 10.1038/s41477-019-0361-8.

Meier, U. (1997). *Growth stages of mono-and dicotyledonous plants*. Blackwell Wissenschafts-Verlag.

Menzel, A., T. H. Sparks, N. Estrella, E. Koch, A. Aasa, R. Ahas, K. Alm-kübler, P. Bissolli, O. BraslavskÁ, A. Briede, F. M. Chmielewski, Z. Crepinsek, Y. Curnel, Å. Dahl, C. Defila, A. Donnelly, Y. Filella, K. Jatczak, F. MÅge, A. Mestre, Ø. Nordli, J. PeÑuelas, P. Pirinen, V. RemiŠovÁ, H. Scheifinger, M. Striz, A. Susnik, A. J. H. V. Vliet, F. emil Wielgolaski, S. Zach, and A. Zust (2006). “European phenological response to climate change matches the warming pattern”. In: *Global Change Biology* 12.10, pp. 1969–1976. DOI: 10.1111/j.1365-2486.2006.01193.x.

Miller, J. G. (1976). “The nature of living systems”. In: *Behavioral Science* 21.5, pp. 295–319.

Minoli, S., D. B. Egli, S. Rolinski, and C. Müller (2019). “Modelling cropping periods of grain crops at the global scale”. In: *Global and Planetary Change* 174, pp. 35–46. DOI: 10.1016/j.gloplacha.2018.12.013.

Minoli, S., C. Müller, J. Elliott, A. C. Ruane, J. Jägermeyr, F. Zabel, M. Dury, C. Folberth, L. Francois, T. Hank, I. Jacquemin, W. Liu, S. Olin, and T. A. M. Pugh (accepted for publication). "Global response patterns of major rainfed crops to adaptation by maintaining current growing periods and irrigation". In: *Earth's Future*. DOI: 10.1029/2018EF001130.

Molotoks, A., E. Stehfest, J. Doelman, F. Albanito, N. Fitton, T. P. Dawson, and P. Smith (2018). "Global projections of future cropland expansion to 2050 and direct impacts on biodiversity and carbon storage". In: *Global Change Biology* 24.12, pp. 5895–5908. DOI: 10.1111/gcb.14459.

Mondal, S., R. P. Singh, J. Crossa, J. Huerta-Espino, I. Sharma, R. Chatrath, G. P. Singh, V. S. Sohu, G. S. Mavi, V. S. P. Sukuru, et al. (2013). "Earliness in wheat: A key to adaptation under terminal and continual high temperature stress in South Asia". In: *Field crops research* 151, pp. 19–26.

Moore, A. D., D. P. Holzworth, N. I. Herrmann, H. E. Brown, P. G. de Voil, V. O. Snow, E. J. Zurcher, and N. I. Huth (2014). "Modelling the manager: Representing rule-based management in farming systems simulation models". In: *Environmental Modelling & Software* 62, pp. 399–410. DOI: 10.1016/j.envsoft.2014.09.001.

Mueller, B., M. Hauser, C. Iles, R. H. Rimi, F. W. Zwiers, and H. Wan (2015). "Lengthening of the growing season in wheat and maize producing regions". In: *Weather and Climate Extremes* 9, pp. 47–56. DOI: 10.1016/j.wace.2015.04.001.

Mueller, N. D., J. S. Gerber, M. Johnston, D. K. Ray, N. Ramankutty, and J. A. Foley (2012). "Closing yield gaps through nutrient and water management". In: *Nature* 490.7419, pp. 254–257. DOI: 10.1038/nature11420.

Muller, B. and P. Martre (2019b). *Plant and crop simulation models: powerful tools to link physiology, genetics, and phenomics.*

Muller, B. and P. Martre (2019a). "Plant and crop simulation models: powerful tools to link physiology, genetics, and phenomics". In: *Journal of Experimental Botany* 70.9, pp. 2339–2344. DOI: 10.1093/jxb/erz175.

Müller, C., J. Elliott, J. Chryssanthacopoulos, A. Arneth, J. Balkovic, P. Ciais, D. Deryng, C. Folberth, M. Glotter, S. Hoek, T. Iizumi, R. C. Izaurralde, C. Jones, N. Khabarov, P. Lawrence, W. Liu, S. Olin, T. A. M. Pugh, D. K. Ray, A. Reddy, C. Rosenzweig, A. C. Ruane, G. Sakurai, E. Schmid, R. Skalsky, C. X. Song, X. Wang, A. de Wit, and H. Yang (2017). "Global gridded crop model evaluation: benchmarking, skills, deficiencies and implications". In: *Geoscientific Model Development* 10.4, pp. 1403–1422. DOI: 10.5194/gmd-10-1403-2017.

Müller, C., J. Elliott, J. Chryssanthacopoulos, A. Arneth, J. Balkovic, P. Ciais, D. Deryng, C. Folberth, M. Glotter, S. Hoek, et al. (2017). "Global gridded crop model evaluation: benchmarking, skills, deficiencies and implications". In: *Geoscientific Model Development Discussions* 10, pp. 1403–1422.

Müller, C., J. Elliott, J. Chryssanthacopoulos, D. Deryng, C. Folberth, T. A. M. Pugh, and E. Schmid (2015). "Implications of climate mitigation for future agricultural production". In: *Environmental Research Letters* 10.12, p. 125004. DOI: 10.1088/1748-9326/10/12/125004.

Müller, C., J. Elliott, D. Kelly, A. Arneth, J. Balkovic, P. Ciais, D. Deryng, C. Folberth, S. Hoek, R. C. Izaurralde, C. D. Jones, N. Khabarov, P. Lawrence, W. Liu, S. Olin, T. A. M. Pugh, A. Reddy, C. Rosenzweig, A. C. Ruane, G. Sakurai, E. Schmid, R. Skalsky, X. Wang, A. de Wit, and H. Yang (2019). "The Global Gridded Crop Model Intercomparison phase 1 simulation dataset". In: *Scientific Data* 6.1. DOI: 10.1038/s41597-019-0023-8.

Müller, C., J. Elliott, and A. Levermann (2014). "Food security: Fertilizing hidden hunger". In: *Nature Climate Change* 4.7, p. 540.

Müller, C. and R. D. Robertson (2013). "Projecting future crop productivity for global economic modeling". In: *Agricultural Economics* 45.1, pp. 37–50. DOI: 10.1111/agec.12088.

Nakamichi, N. (2014). "Adaptation to the Local Environment by Modifications of the Photoperiod Response in Crops". In: *Plant and Cell Physiology* 56.4, pp. 594–604. DOI: 10.1093/pcp/pcu181.

Nelson, G. C., H. Valin, R. D. Sands, P. Havlík, H. Ahammad, D. Deryng, J. Elliott, S. Fujimori, T. Hasegawa, E. Heyhoe, P. Kyle, M. V. Lampe, H. Lotze-Campen, D. M. d'Croz, H. van Meijl, D. van der Mensbrugghe, C. Müller, A. Popp, R. Robertson, S. Robinson, E. Schmid, C. Schmitz, A. Tabeau, and D. Willenbockel (2013). "Climate change effects on agriculture: Economic responses to biophysical shocks". In: *Proceedings of the National Academy of Sciences* 111.9, pp. 3274–3279. DOI: 10.1073/pnas.1222465110.

Nishina, K., A. Ito, N. Hanasaki, and S. Hayashi (2017). "Reconstruction of spatially detailed global map of NH_4^+ and NO_3^-NO application in synthetic nitrogen fertilizer". In: *Earth System Science Data* 9.1, pp. 149–162. DOI: 10.5194/essd-9-149-2017.

Olatinwo, R. and G. Hoogenboom (2014). "Weather-based pest forecasting for efficient crop protection". In: *Integrated Pest Management.* Elsevier, pp. 59–78.

Olesen, J. E., C. D. Børgesen, L. Elsgaard, T. Palosuo, R. P. Rötter, A. O. Skjelvåg, P. Peltonen-Sainio, T. Börjesson, M. Trnka, F. Ewert, S. Siebert, N. Brisson, J. Eitzinger, E. D. van Asselt, M. Oberforster, and H. J. van der Fels-Klerx (2012). "Changes in time of sowing, flowering and maturity of cereals in Europe under climate change". In: *Food Additives & Contaminants: Part A* 29.10, pp. 1527–1542. DOI: 10.1080/19440049.2012.712060.

Olesen, J. E., M. Trnka, K. C. Kersebaum, A. Skjelvåg, B. Seguin, P. Peltonen-Sainio, F Rossi, J. Kozyra, and F. Micale (2011). "Impacts and adaptation of European crop production systems to climate change". In: *European Journal of Agronomy* 34.2, pp. 96–112.

Olin, S., G. Schurgers, M. Lindeskog, D. Wårlind, B. Smith, P. Bodin, J. Holmér, and A. Arneth (2015). "Modelling the response of yields and tissue C: N to changes in atmospheric CO 2 and N management in the main wheat regions of western Europe". In: *Biogeosciences* 12.8, pp. 2489–2515.

Parent, B., O. Turc, Y. Gibon, M. Stitt, and F. Tardieu (2010). "Modelling temperature-compensated physiological rates, based on the co-ordination of responses to temperature of developmental processes". In: *Journal of Experimental Botany* 61.8, pp. 2057–2069.

Parent, B., J. Bonneau, L. Maphosa, A. Kovalchuk, P. Langridge, and D. Fleury (2017). "Quantifying Wheat Sensitivities to Environmental Constraints to Dissect Genotype × Environment Interactions in the Field". In: *Plant Physiology* 174.3, pp. 1669–1682. DOI: 10.1104/pp.17.00372.

Parent, B., M. Leclere, S. Lacube, M. A. Semenov, C. Welcker, P. Martre, and F. Tardieu (2018). “Maize yields over Europe may increase in spite of climate change, with an appropriate use of the genetic variability of flowering time”. In: *Proceedings of the National Academy of Sciences* 115.42, pp. 10642–10647. DOI: 10.1073/pnas.1720716115.

Parent, B. and F. Tardieu (2012). “Temperature responses of developmental processes have not been affected by breeding in different ecological areas for 17 crop species”. In: *New Phytologist* 194.3, pp. 760–774.

Passioura, J. B. and J. F. Angus (2010). “Improving productivity of crops in water-limited environments”. In: *Advances in agronomy*. Vol. 106. Elsevier, pp. 37–75.

Passioura, J. (2006). “Increasing crop productivity when water is scarce—from breeding to field management”. In: *Agricultural water management* 80.1-3, pp. 176–196.

Peltonen-Sainio, P., A. Rajala, H. Känkänen, and K. Hakala (2015). “Improving farming systems in northern Europe”. In: *Crop Physiology*. Elsevier, pp. 65–91. DOI: 10.1016/b978-0-12-417104-6.00004-2.

Pierce, D. (2015). *ncdf4: Interface to Unidata netCDF (Version 4 or Earlier) Format Data Files*. R package version 1.15.

Pirttioja, N., T. R. Carter, S. Fronzek, M. Bindi, H. Hoffmann, T. Palosuo, M. Ruiz-Ramos, F. Tao, M. Trnka, M. Acutis, et al. (2015). “Temperature and precipitation effects on wheat yield across a European transect: a crop model ensemble analysis using impact response surfaces”. In: *Climate Research* 65, pp. 87–105.

Pongratz, J., H. Dolman, A. Don, K.-H. Erb, R. Fuchs, M. Herold, C. Jones, T. Kuemmerle, S. Luyssaert, P. Meyfroidt, and K. Naudts (2017). “Models meet data: Challenges and opportunities in implementing land management in Earth system models”. In: *Global Change Biology* 24.4, pp. 1470–1487. DOI: 10.1111/gcb.13988.

Popp, A., K. Calvin, S. Fujimori, P. Havlik, F. Humpenöder, E. Stehfest, B. L. Bodirsky, J. P. Dietrich, J. C. Doelmann, M. Gusti, T. Hasegawa, P. Kyle, M. Obersteiner, A. Tabeau, K. Takahashi, H. Valin, S. Waldhoff, I. Weindl, M. Wise, E. Kriegler, H. Lotze-Campen, O. Fricko, K. Riahi, and D. P. van Vuuren (2017). “Land-use futures in the shared socio-economic pathways”. In: *Global Environmental Change* 42, pp. 331–345. DOI: 10.1016/j.gloenvcha.2016.10.002.

Porter, J. R., X. Liyong, A. Challinor, K. Cochrane, M. Howden, M. M. Iqbal, D. Lobell, and M. I. Travasso (2014). *Chapter 7: food security and food production systems. IPCC 2014: climate change 2014: impacts, adaptation, and vulnerability. Contribution of working group II to the fifth assessment report of the intergovernmental panel on climate change. Final draft. IPCC AR5 WGII.*

Porter, J. R. and M. Gawith (1999a). “Temperatures and the growth and development of wheat: a review”. In: *European journal of agronomy* 10.1, pp. 23–36.

Porter, J. R. and M. Gawith (1999b). “Temperatures and the growth and development of wheat: a review”. In: *European Journal of Agronomy* 10.1, pp. 23–36. DOI: 10.1016/s1161-0301(98)00047-1.

Porter, J. R., M. Howden, and P. Smith (2017). “Considering agriculture in IPCC assessments”. In: *Nature Climate Change* 7.Commentary, pp. 680–683.

Porter, J. R. and M. A. Semenov (2005). “Crop responses to climatic variation”. In: *Philosophical Transactions of the Royal Society B: Biological Sciences* 360.1463, pp. 2021–2035. DOI: 10.1098/rstb.2005.1752.

Portmann, F. T., S. Siebert, and P. Döll (2010). “MIRCA2000-Global monthly irrigated and rainfed crop areas around the year 2000: A new high-resolution data set for agricultural and hydrological modeling”. In: *Global Biogeochemical Cycles* 24.1, n/a–n/a. DOI: 10.1029/2008gb003435.

Porwollik, V., C. Müller, J. Elliott, J. Chryssanthacopoulos, T. Iizumi, D. K. Ray, A. C. Ruane, A. Arneth, J. Balkovič, P. Ciais, D. Deryng, C. Folberth, R. C. Izaurralde, C. D. Jones, N. Khabarov, P. J. Lawrence, W. Liu, T. A. Pugh, A. Reddy, G. Sakurai, E. Schmid, X. Wang, A. de Wit, and X. Wu (2017). “Spatial and temporal uncertainty of crop yield aggregations”. In: *European Journal of Agronomy* 88, pp. 10–21. DOI: 10.1016/j.eja.2016.08.006.

Porwollik, V., S. Rolinski, J. Heinke, and C. Müller (2019). “Generating a rule-based global gridded tillage dataset”. In: *Earth System Science Data* 11.2, pp. 823–843. DOI: 10.5194/essd-11-823-2019.

Powers, S. M., R. B. Chowdhury, G. K. MacDonald, G. S. Metson, A. H. W. Beusen, A. F. Bouwman, S. E. Hampton, B. K. Mayer, M. L. McCrackin, and D. A. Vaccari (2019). “Global Opportunities to Increase Agricultural Independence Through Phosphorus Recycling”. In: *Earth's Future* 7.4, pp. 370–383. DOI: 10.1029/2018ef001097.

Prasad, P. V., K. J. Boote, and L. H. Allen Jr (2006). “Adverse high temperature effects on pollen viability, seed-set, seed yield and harvest index of grain-sorghum [Sorghum bicolor (L.) Moench] are more severe at elevated carbon dioxide due to higher tissue temperatures”. In: *Agricultural and forest meteorology* 139.3-4, pp. 237–251.

Pretty, J. (2007). “Agricultural sustainability: concepts, principles and evidence”. In: *Philosophical Transactions of the Royal Society B: Biological Sciences* 363.1491, pp. 447–465. DOI: 10.1098/rstb.2007.2163.

Pretty, J. (2008). “Agricultural sustainability: concepts, principles and evidence”. In: *Philosophical Transactions of the Royal Society B: Biological Sciences* 363.1491, pp. 447–465. DOI: 10.1098/rstb.2007.2163.

Priestley, C. H. B. and R. Taylor (1972). “On the assessment of surface heat flux and evaporation using large-scale parameters”. In: *Monthly weather review* 100.2, pp. 81–92.

Pugh, T. A. M., C. Müller, J. Elliott, D. Deryng, C. Folberth, S. Olin, E. Schmid, and A. Arneth (2016). “Climate analogues suggest limited potential for intensification of production on current croplands under climate change”. In: *Nature Communications* 7, pp. 1–8. ISSN: 20411723. DOI: 10.1038/ncomms12608.

R Core Team (2018). *R: A Language and Environment for Statistical Computing*. R Foundation for Statistical Computing. Vienna, Austria.

Rasmussen, L. V., B. Coolsaet, A. Martin, O. Mertz, U. Pascual, E. Corbera, N. Dawson, J. A. Fisher, P. Franks, and C. M. Ryan (2018). “Social-ecological outcomes of agricultural intensification”. In: *Nature Sustainability* 1.6, pp. 275–282. DOI: 10.1038/s41893-018-0070-8.

Ray, D. K., N. D. Mueller, P. C. West, and J. A. Foley (2013). "Yield Trends Are Insufficient to Double Global Crop Production by 2050". In: *PLoS ONE* 8.6. Ed. by J. P. Hart, e66428. DOI: 10.1371/journal.pone.0066428.

Ray, D. K., N. Ramankutty, N. D. Mueller, P. C. West, and J. A. Foley (2012). "Recent patterns of crop yield growth and stagnation". In: *Nature Communications* 3.1. DOI: 10.1038/ncomms2296.

Rezaei, E. E., S. Siebert, and F. Ewert (2015). "Intensity of heat stress in winter wheat—phenology compensates for the adverse effect of global warming". In: *Environmental Research Letters* 10.2, p. 024012. DOI: 10.1088/1748-9326/10/2/024012.

Rezaei, E. E., S. Siebert, and F. Ewert (2017). "Climate and management interaction cause diverse crop phenology trends". In: *Agricultural and Forest Meteorology* 233, pp. 55–70. DOI: 10.1016/j.agrformet.2016.11.003.

Rezaei, E. E., S. Siebert, H. Hüging, and F. Ewert (2018). "Climate change effect on wheat phenology depends on cultivar change". In: *Scientific Reports* 8.1. DOI: 10.1038/s41598-018-23101-2.

Rezaei, E. E., H. Webber, T. Gaiser, J. Naab, and F. Ewert (2015). "Heat stress in cereals: mechanisms and modelling". In: *European Journal of Agronomy* 64, pp. 98–113.

Ritchie, J. T. and D. S. Nesmith (1991). "Temperature and Crop Development". In: *Modeling Plant and Soil Systems*. American Society of Agronomy, Crop Science Society of America, Soil Science Society of America. DOI: 10.2134/agronmonogr31.c2.

Roberts, E. H., R. J. Summerfield, and R. H. Ellis (1997). "Reproductive development and crop adaptation". In: *Journal of Biological Education* 31.2, pp. 97–105.

Robinson, G. (2014). *Geographies of agriculture: globalisation, restructuring and sustainability*. Routledge.

Rockström, J., W. Steffen, K. Noone, Å. Persson, F. S. Chapin III, E. F. Lambin, T. M. Lenton, M. Scheffer, C. Folke, H. J. Schellnhuber, et al. (2009a). "A safe operating space for humanity". In: *nature* 461.7263, p. 472.

Rockström, J., W. L. Steffen, K. Noone, Å. Persson, F. S. I. Chapin, E. Lambin, T. M. Lenton, M. Scheffer, C. Folke, H. J. Schellnhuber, et al. (2009b). "Planetary boundaries: exploring the safe operating space for humanity". In: *Ecology and society*.

Rojas, M., F. Lambert, J. Ramirez-Villegas, and A. J. Challinor (2019). "Emergence of robust precipitation changes across crop production areas in the 21st century". In: *Proceedings of the National Academy of Sciences* 116.14, pp. 6673–6678. DOI: 10.1073/pnas.1811463116.

Rosenzweig, C., J. Elliott, D. Deryng, A. C. Ruane, C. Müller, A. Arneth, K. J. Boote, C. Folberth, M. Glotter, N. Khabarov, K. Neumann, F. Piontek, T. A. M. Pugh, E. Schmid, E. Stehfest, H. Yang, and J. W. Jones (2014). "Assessing agricultural risks of climate change in the 21st century in a global gridded crop model intercomparison". In: *Proceedings of the National Academy of Sciences* 111.9, pp. 3268–3273. DOI: 10.1073/pnas.1222463110.

Rosenzweig, C., J. W. Jones, J. L. Hatfield, A. C. Ruane, K. J. Boote, P. Thorburn, J. M. Antle, G. C. Nelson, C. Porter, S. Janssen, et al. (2013). "The agricultural model intercomparison and improvement project (AgMIP): protocols and pilot studies". In: *Agricultural and Forest Meteorology* 170, pp. 166–182.

Rosenzweig, C., A. C. Ruane, J. Antle, J. Elliott, M. Ashfaq, A. A. Chatta, F. Ewert, C. Folberth, I. Hathie, P. Havlik, et al. (2018). "Coordinating AgMIP data and models across global and regional scales for 1.5° C and 2.0° C assessments". In: *Phil. Trans. R. Soc. A* 376.2119, p. 20160455.

Rötter, R. P., M. P. Hoffmann, M. Koch, and C. Müller (2018). "Progress in modelling agricultural impacts of and adaptations to climate change". In: *Current Opinion in Plant Biology* 45, pp. 255–261. DOI: 10.1016/j.pbi.2018.05.009.

Rötter, R. P., T. R. Carter, J. E. Olesen, and J. R. Porter (2011). "Crop–climate models need an overhaul". In: *Nature climate change* 1.4, p. 175.

Rötter, R. P., J. Höhn, M. Trnka, S. Fronzek, T. R. Carter, and H. Kahiluoto (2013). "Modelling shifts in agroclimate and crop cultivar response under climate change". In: *Ecology and Evolution* 3.12, pp. 4197–4214. DOI: 10.1002/ece3.782.

Ruane, A. C., R. Goldberg, and J. Chryssanthacopoulos (2015). "Climate forcing datasets for agricultural modeling: Merged products for gap-filling and historical climate series estimation". In: *Agricultural and Forest Meteorology* 200, pp. 233–248. DOI: 10.1016/j.agrformet.2014.09.016.

Ruiz-Ramos, M., R. Ferrise, A. Rodríguez, I. J. Lorite, M. Bindi, T. R. Carter, S. Fronzek, T. Palosuo, N. Pirttioja, P. Baranowski, et al. (2018). "Adaptation response surfaces for managing wheat under perturbed climate and CO2 in a Mediterranean environment". In: *Agricultural Systems* 159, pp. 260–274.

Rukhovich, D. I., P. V. Koroleva, E. V. Vilchevskaya, V. A. Romanenkov, and L. G. Kolesnikova (2007). "Constructing a spatially-resolved database for modelling soil organic carbon stocks of croplands in European Russia". In: *Regional Environmental Change* 7.2, pp. 51–61.

Sacks, W. J., D. Deryng, J. A. Foley, and N. Ramankutty (2010). "Crop planting dates: an analysis of global patterns". In: *Global Ecology and Biogeography*, no–no. DOI: 10.1111/j.1466-8238.2010.00551.x.

Sacks, W. J. and C. J. Kucharik (2011). "Crop management and phenology trends in the US Corn Belt: Impacts on yields, evapotranspiration and energy balance". In: *Agricultural and Forest Meteorology* 151.7, pp. 882–894.

Sage, R. F. and D. S. Kubien (2007). "The temperature response of C_3 and C_4 photosynthesis". In: *Plant, Cell & Environment* 30.9, pp. 1086–1106. DOI: 10.1111/j.1365-3040.2007.01682.x.

Sánchez, B., A. Rasmussen, and J. R. Porter (2014). "Temperatures and the growth and development of maize and rice: a review". In: *Global Change Biology* 20.2, pp. 408–417. DOI: 10.1111/gcb.12389.

Schaphoff, S., W. von Bloh, A. Rammig, K. Thonicke, H. Biemans, M. Forkel, D. Gerten, J. Heinke, J. Jägermeyr, J. Knauer, F. Langerwisch, W. Lucht, C. Müller, S. Rolinski, and K. Waha (2018). "LPJmL4 – a dynamic global vegetation model with managed land – Part 1: Model description". In: *Geoscientific Model Development* 11.4, pp. 1343–1375. DOI: 10.5194/gmd-11-1343-2018.

Schauberger, B., S. Archontoulis, A. Arneth, J. Balkovic, P. Ciais, D. Deryng, J. Elliott, C. Folberth, N. Khabarov, C. Müller, T. A. M. Pugh, S. Rolinski, S. Schaphoff, E. Schmid,

X. Wang, W. Schlenker, and K. Frieler (2017). “Consistent negative response of US crops to high temperatures in observations and crop models”. In: *Nature Communications* 8.1. DOI: 10.1038/ncomms13931.

Schauberger, B., S. Rolinski, and C. Müller (2016). “A network-based approach for semi-quantitative knowledge mining and its application to yield variability”. In: *Environmental Research Letters* 11.12, p. 123001. DOI: 10.1088/1748-9326/11/12/123001.

Schellnhuber, H. J. (1999). “‘Earth system’analysis and the second Copernican revolution”. In: *Nature* 402.6761supp, p. C19.

Schellnhuber, H. J., K. Frieler, and P. Kabat (2013). “The elephant, the blind, and the intersectoral intercomparison of climate impacts: Fig. 1.” In: *Proceedings of the National Academy of Sciences* 111.9, pp. 3225–3227. DOI: 10.1073/pnas.1321791111.

Schiere, J. B. H., I. Darnhofer, and M. Duru (2012). “Dynamics in farming systems: of changes and choices”. In: *Farming Systems Research into the 21st century: The new dynamic*. Springer, pp. 337–363.

Schils, R. L. M., J. L. Ellis, C. A. M. De Klein, J. P. Lesschen, S. O. Petersen, and S. G. Sommer (2012). “Mitigation of greenhouse gases from agriculture: Role of models”. In: *Acta Agriculturae Scandinavica, Section A–Animal Science* 62.4, pp. 212–224.

Schleussner, C.-F., D. Deryng, C. Müller, J. Elliott, F. Saeed, C. Folberth, W. Liu, X. Wang, T. A. Pugh, W. Thiery, et al. (2018). “Crop productivity changes in 1.5 C and 2 C worlds under climate sensitivity uncertainty”. In: *Environmental Research Letters* 13.6, p. 064007.

Schmitz, C., U. Kreidenweis, H. Lotze-Campen, A. Popp, M. Krause, J. P. Dietrich, and C. Müller (2014). “Agricultural trade and tropical deforestation: interactions and related policy options”. In: *Regional Environmental Change* 15.8, pp. 1757–1772. DOI: 10.1007/s10113-014-0700-2.

Sedgley, R. (1991). “An appraisal of the Donald ideotype after 21 years”. In: *Field Crops Research* 26.2, pp. 93–112. DOI: 10.1016/0378-4290(91)90031-p.

Semenov, M. A., P. Stratonovitch, F. Alghabari, and M. J. Gooding (2014). “Adapting wheat in Europe for climate change”. In: *Journal of Cereal Science* 59.3, pp. 245–256.

Siebert, S., M. Kummu, M. Porkka, P. Döll, N. Ramankutty, and B. R. Scanlon (2015). “A global data set of the extent of irrigated land from 1900 to 2005”. In: *Hydrology and Earth System Sciences* 19.3, pp. 1521–1545. DOI: 10.5194/hess-19-1521-2015.

Siebert, S., F. T. Portmann, and P. Döll (2010). “Global Patterns of Cropland Use Intensity”. In: *Remote Sensing* 2.7, pp. 1625–1643. DOI: 10.3390/rs2071625.

Siebert, S., H. Webber, G. Zhao, and F. Ewert (2017). “Heat stress is overestimated in climate impact studies for irrigated agriculture”. In: *Environmental Research Letters* 12.5, p. 054023.

Singh, R. P., P. V. V. Prasad, and K. R. Reddy (2013). “Impacts of Changing Climate and Climate Variability on Seed Production and Seed Industry”. In: *Advances in Agronomy*. Elsevier, pp. 49–110. DOI: 10.1016/b978-0-12-405942-9.00002-5.

Slafer, G. A., A. G. Kantolic, M. L. Appendino, G. Tranquilli, D. J. Miralles, and R. Savin (2015). “Genetic and environmental effects on crop development determining adaptation and yield”. In: *Crop Physiology*. Elsevier, pp. 285–319. DOI: 10.1016/b978-0-12-417104-6.00012-1.

Smith, N. G. and J. S. Dukes (2013). “Plant respiration and photosynthesis in global-scale models: incorporating acclimation to temperature and CO 2”. In: *Global Change Biology* 19.1, pp. 45–63.

Steffen, W., K. Richardson, J. Rockström, S. E. Cornell, I. Fetzer, E. M. Bennett, R. Biggs, S. R. Carpenter, W. de Vries, C. A. de Wit, C. Folke, D. Gerten, J. Heinke, G. M. Mace, L. M. Persson, V. Ramanathan, B. Reyers, and S. Sorlin (2015). “Planetary boundaries: Guiding human development on a changing planet”. In: *Science* 347.6223, pp. 1259855–1259855. DOI: 10.1126/science.1259855.

Steffen, W., P. J. Crutzen, and J. R. McNeill (2007). “The Anthropocene: are humans now overwhelming the great forces of nature”. In: *AMBIO: A Journal of the Human Environment* 36.8, pp. 614–622.

Steffen, W., R. Leinfelder, J. Zalasiewicz, C. N. Waters, M. Williams, C. Summerhayes, A. D. Barnosky, A. Cearreta, P. Crutzen, M. Edgeworth, E. C. Ellis, I. J. Fairchild, A. Galuszka, J. Grinevald, A. Haywood, J. I. do Sul, C. Jeandel, J. McNeill, E. Odada, N. Oreskes, A. Revkin, D. deB. Richter, J. Syvitski, D. Vidas, M. Wagreich, S. L. Wing, A. P. Wolfe, and H. Schellnhuber (2016). “Stratigraphic and Earth System approaches to defining the Anthropocene”. In: *Earth's Future* 4.8, pp. 324–345. DOI: 10.1002/2016ef000379.

Stevanović, M., A. Popp, H. Lotze-Campen, J. P. Dietrich, C. Müller, M. Bonsch, C. Schmitz, B. L. Bodirsky, F. Humpenöder, and I. Weindl (2016). “The impact of high-end climate change on agricultural welfare”. In: *Science Advances* 2.8, e1501452. DOI: 10.1126/sciadv.1501452.

Strong, D. R. and K. T. Frank (2010). “Human Involvement in Food Webs”. In: *Annual Review of Environment and Resources* 35.1, pp. 1–23. DOI: 10.1146/annurev-environ-031809-133103.

Summerfield, R. J., R. H. Ellis, and P. Q. Craufurd (1996). “Phenological adaptation to cropping environment. From evaluation descriptors of times to flowering to the genetic characterisation of flowering responses to photoperiod and temperature”. In: *Euphytica* 92.1-2, pp. 281–286.

Tack, J., A. Barkley, and N. Hendricks (2017). “Irrigation offsets wheat yield reductions from warming temperatures”. In: *Environmental Research Letters* 12.11, p. 114027.

Tao, F., S. Zhang, Z. Zhang, and R. P. Rötter (2014). “Maize growing duration was prolonged across China in the past three decades under the combined effects of temperature, agronomic management, and cultivar shift”. In: *Global Change Biology* 20.12, pp. 3686–3699. DOI: 10.1111/gcb.12684.

Taylor, K. E., R. J. Stouffer, and G. A. Meehl (2012). “An Overview of CMIP5 and the Experiment Design”. In: *Bulletin of the American Meteorological Society* 93.4, pp. 485–498. DOI: 10.1175/bams-d-11-00094.1.

Teixeira, E. I., G. Fischer, H. van Velthuizen, C. Walter, and F. Ewert (2013). “Global hot-spots of heat stress on agricultural crops due to climate change”. In: *Agricultural and Forest Meteorology* 170, pp. 206–215. DOI: 10.1016/j.agrformet.2011.09.002.

Thornthwaite, C. W. (1948). “An Approach toward a Rational Classification of Climate”. In: *Geographical Review* 38.1, p. 55. DOI: 10.2307/210739.

Tilman, D., C. Balzer, J. Hill, and B. L. Befort (2011). "Global food demand and the sustainable intensification of agriculture". In: *Proceedings of the National Academy of Sciences* 108.50, pp. 20260–20264. DOI: 10.1073/pnas.1116437108.

Tomich, T. P., S. Brodt, H. Ferris, R. Galt, W. R. Horwath, E. Kebreab, J. H. Leveau, D. Liptzin, M. Lubell, P. Merel, R. Michelmore, T. Rosenstock, K. Scow, J. Six, N. Williams, and L. Yang (2011). "Agroecology: A Review from a Global-Change Perspective". In: *Annual Review of Environment and Resources* 36.1, pp. 193–222. DOI: 10.1146/annurev-environ-012110-121302.

Trevaskis, B., M. N. Hemming, E. S. Dennis, and W. J. Peacock (2007). "The molecular basis of vernalization-induced flowering in cereals". In: *Trends in Plant Science* 12.8, pp. 352–357. DOI: 10.1016/j.tplants.2007.06.010.

UNFCCC, U. (2015). *Decision 1/CP.21. The Paris Agreement.* available at: https://unfccc.int/process-and-meetings/the-paris-agreement/the-paris-agreement, accessed on: 22nd August 2019.

United Nations (2015a). *Transforming our world: the 2030 Agenda for Sustainable Development.* available at: https://sustainabledevelopment.un.org/post2015/transformingourworld, accessed on: 19th August 2019.

United Nations (2015b). "World population prospects: The 2015 revision". In: *United Nations Econ Soc Aff* 33.2, pp. 1–66.

van Bussel, L. G. J., E. Stehfest, S. Siebert, C. Müller, and F. Ewert (2015). "Simulation of the phenological development of wheat and maize at the global scale". In: *Global Ecology and Biogeography* 24.9, pp. 1018–1029. DOI: 10.1111/geb.12351.

van Vuuren, D. P., J. Lowe, E. Stehfest, L. Gohar, A. F. Hof, C. Hope, R. Warren, M. Meinshausen, and G.-K. Plattner (2009). "How well do integrated assessment models simulate climate change?" In: *Climatic Change* 104.2, pp. 255–285. DOI: 10.1007/s10584-009-9764-2.

van Wart, J., L. G. J. van Bussel, J. Wolf, R. Licker, P. Grassini, A. Nelson, H. Boogaard, J. Gerber, N. D. Mueller, L. Claessens, M. K. van Ittersum, and K. G. Cassman (2013). "Use of agro-climatic zones to upscale simulated crop yield potential". In: *Field Crops Research* 143, pp. 44–55. DOI: 10.1016/j.fcr.2012.11.023.

Vasey, D. E. (2002). *An ecological history of agriculture 10,000 BC-AD 10,000.* Purdue University Press.

Verburg, P. H., E. C. Ellis, and A. Letourneau (2011). "A global assessment of market accessibility and market influence for global environmental change studies". In: *Environmental Research Letters* 6.3, p. 034019. DOI: 10.1088/1748-9326/6/3/034019.

Vermeulen, S. J., B. M. Campbell, and J. S. Ingram (2012). "Climate Change and Food Systems". In: *Annual Review of Environment and Resources* 37.1, pp. 195–222. DOI: 10.1146/annurev-environ-020411-130608.

Vermeulen, S. J., D. Dinesh, S. M. Howden, L. Cramer, and P. K. Thornton (2018). "Transformation in Practice: A Review of Empirical Cases of Transformational Adaptation in Agriculture Under Climate Change". In: *Frontiers in Sustainable Food Systems* 2. DOI: 10.3389/fsufs.2018.00065.

von Bloh, W., S. Schaphoff, C. Müller, S. Rolinski, K. Waha, and S. Zaehle (2018). "Implementing the nitrogen cycle into the dynamic global vegetation, hydrology and crop growth model LPJmL (version 5)". In: *Geoscientific Model Development* 11, pp. 2789–2812.

von Caemmerer, S. (2000). *Biochemical models of leaf photosynthesis.* Csiro publishing.

Voss-Fels, K. P., A. Stahl, B. Wittkop, C. Lichthardt, S. Nagler, T. Rose, T.-W. Chen, H. Zetzsche, S. Seddig, M. M. Baig, A. Ballvora, M. Frisch, E. Ross, B. J. Hayes, M. J. Hayden, F. Ordon, J. Leon, H. Kage, W. Friedt, H. Stützel, and R. J. Snowdon (2019). "Breeding improves wheat productivity under contrasting agrochemical input levels". In: *Nature Plants* 5.7, pp. 706–714. DOI: 10.1038/s41477-019-0445-5.

Vreugdenhil, M., W. Wagner, B. Bauer-Marschallinger, I. Pfeil, I. Teubner, C. Rüdiger, and P. Strauss (2018). "Sensitivity of Sentinel-1 Backscatter to Vegetation Dynamics: An Austrian Case Study". In: *Remote Sensing* 10.9, p. 1396. DOI: 10.3390/rs10091396.

Waha, K., C. Müller, A. Bondeau, J. Dietrich, P. Kurukulasuriya, J. Heinke, and H. Lotze-Campen (2013). "Adaptation to climate change through the choice of cropping system and sowing date in sub-Saharan Africa". In: *Global Environmental Change* 23.1, pp. 130–143. DOI: 10.1016/j.gloenvcha.2012.11.001.

Waha, K., L. G. J. van Bussel, C. Müller, and A. Bondeau (2012). "Climate-driven simulation of global crop sowing dates". In: *Global Ecology and Biogeography* 21.2, pp. 247–259. DOI: 10.1111/j.1466-8238.2011.00678.x.

Walker, B., C. S. Holling, S. Carpenter, and A. Kinzig (2004). "Resilience, adaptability and transformability in social–ecological systems". In: *Ecology and society* 9.2.

Wang, E. et al. (2017). "The uncertainty of crop yield projections is reduced by improved temperature response functions". In: *Nature Plants* 3.8. DOI: 10.1038/nplants.2017.102.

Webber, H., P. Martre, S. Asseng, B. Kimball, J. White, M. Ottman, G. W. Wall, G. De Sanctis, J. Doltra, R. Grant, et al. (2017). "Canopy temperature for simulation of heat stress in irrigated wheat in a semi-arid environment: A multi-model comparison". In: *Field Crops Research* 202, pp. 21–35.

White, J. W., B. A. Kimball, G. W. Wall, and M. J. Ottman (2012). "Cardinal temperatures for wheat leaf appearance as assessed from varied sowing dates and infrared warming". In: *Field Crops Research* 137, pp. 213–220.

Wickham, H. (2009). *ggplot2: Elegant Graphics for Data Analysis.* Springer-Verlag New York. ISBN: 978-0-387-98140-6.

Wickham, H. (2011). "The Split-Apply-Combine Strategy for Data Analysis". In: *Journal of Statistical Software* 40.1, pp. 1–29.

Willett, W., J. Rockström, B. Loken, M. Springmann, T. Lang, S. Vermeulen, T. Garnett, D. Tilman, F. DeClerck, A. Wood, M. Jonell, M. Clark, L. J. Gordon, J. Fanzo, C. Hawkes, R. Zurayk, J. A. Rivera, W. D. Vries, L. M. Sibanda, A. Afshin, A. Chaudhary, M. Herrero, R. Agustina, F. Branca, A. Lartey, S. Fan, B. Crona, E. Fox, V. Bignet, M. Troell, T. Lindahl, S. Singh, S. E. Cornell, K. S. Reddy, S. Narain, S. Nishtar, and C. J. L. Murray (2019). "Food in the Anthropocene: the EAT–Lancet Commission on healthy diets from sustainable food systems". In: *The Lancet* 393.10170, pp. 447–492. DOI: 10.1016/s0140-6736(18)31788-4.

Wirsenius, S. (2000). *Human use of land and organic materials: modeling the turnover of biomass in the global food system.* Chalmers University of Technology.

Wolf, J., T. O. West, Y. L. Page, G. P. Kyle, X. Zhang, G. J. Collatz, and M. L. Imhoff (2015). "Biogenic carbon fluxes from global agricultural production and consumption". In: *Global Biogeochemical Cycles* 29.10, pp. 1617–1639. DOI: 10.1002/2015gb005119.

Yamori, W., K. Hikosaka, and D. A. Way (2014). "Temperature response of photosynthesis in C 3, C 4, and CAM plants: temperature acclimation and temperature adaptation". In: *Photosynthesis research* 119.1-2, pp. 101–117.

Zarco-Tejada, P. J., N. Hubbard, and P. Loudjani (2014). "Precision agriculture: An opportunity for EU farmers—potential support with the CAP 2014-2020". In: *Joint Research Centre (JRC) of the European Commission.*

Zeng, N., F. Zhao, G. J. Collatz, E. Kalnay, R. J. Salawitch, T. O. West, and L. Guanter (2014). "Agricultural Green Revolution as a driver of increasing atmospheric CO2 seasonal amplitude". In: *Nature* 515.7527, pp. 394–397. DOI: 10.1038/nature13893.

Zhao, C., B. Liu, S. Piao, X. Wang, D. B. Lobell, Y. Huang, M. Huang, Y. Yao, S. Bassu, P. Ciais, J.-L. Durand, J. Elliott, F. Ewert, I. A. Janssens, T. Li, E. Lin, Q. Liu, P. Martre, C. Müller, S. Peng, J. Peñuelas, A. C. Ruane, D. Wallach, T. Wang, D. Wu, Z. Liu, Y. Zhu, Z. Zhu, and S. Asseng (2017). "Temperature increase reduces global yields of major crops in four independent estimates". In: *Proceedings of the National Academy of Sciences*, p. 201701762. ISSN: 0027-8424. DOI: 10.1073/pnas.1701762114.

Zhu, P., Q. Zhuang, S. V. Archontoulis, C. Bernacchi, and C. Müller (2019). "Dissecting the nonlinear response of maize yield to high temperature stress with model-data integration". In: *Global change biology.*

Zimmermann, A., H. Webber, G. Zhao, F. Ewert, J. Kros, J. Wolf, W. Britz, and W. de Vries (2017). "Climate change impacts on crop yields, land use and environment in response to crop sowing dates and thermal time requirements". In: *Agricultural Systems* 157, pp. 81–92. DOI: 10.1016/j.agsy.2017.07.007.

Declaration

I hereby declare that I completed the doctoral thesis independently based on the stated resources and aids. I have not applied for a doctoral degree elsewhere and do not have a corresponding doctoral degree. I have not submitted the doctoral thesis, or parts of it, to another academic institution and the thesis has not been accepted or rejected. I declare that I have acknowledged the Doctoral Degree Regulations which underlie the procedure of the Faculty of Life Sciences of Humboldt-Universität zu Berlin, as amended on 5^{th} March 2015. Furthermore, I declare that no collaboration with commercial doctoral degree supervisors took place, and that the principles of Humboldt-Universität zu Berlin for ensuring good academic practice were abided by.

Erklärung

Hiermit erkläre ich, die Dissertation selbstständig und nur unter Verwendung der angegebenen Hilfen und Hilfsmittel angefertigt zu haben. Ich habe mich anderwärts nicht um einen Doktorgrad beworben und besitze keinen entsprechenden Doktorgrad. Ich erkläre, dass ich die Dissertation oder Teile davon nicht bereits bei einer anderen wissenschaftlichen Einrichtung eingereicht habe und dass sie dort weder angenommen noch abgelehnt wurde. Ich erkläre die Kenntnisnahme der dem Verfahren zugrunde liegenden Promotionsordnung der Lebenswissenschaftlichen Fakultät der Humboldt-Universität zu Berlin vom 5. März 2015. Weiterhin erkläre ich, dass keine Zusammenarbeit mit gewerblichen Promotionsbearbeiterinnen/Promotionsberatern stattgefunden hat und dass die Grundsätze der Humboldt-Universität zu Berlin zur Sicherung guter wissenschaftlicher Praxis eingehalten wurden.

Berlin, ____________________ ____________________

Date | Datum Signature | Unterschrift